Do Funds Window Dress?
Evidence for U.S. Domestic Equity Mutual Funds

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January 28, 2004

Abstract

"Window dressing" is the practice by fund managers of adjusting a fund's portfolio composition immediately before disclosing the holdings to the public at the end of the quarter. The common wisdom on the street and in the financial press is that window dressing activity has become widespread as investors have become increasingly sophisticated in analyzing fund holdings as well as past returns in an effort to detect skill. So far there has been little empirical evidence on mutual funds in the academic literature to this effect. We analyze the semi-annual holdings and daily net asset values of 4,025 U.S. domestic equity mutual funds over the period from 1997 to 2002 and find strong evidence of window dressing. In particular, a substantial fraction of funds report holdings that are very misleading due to window dressing activity. We show that growth funds and funds with poor recent performance are more likely to be window dressers. Furthermore, the window dressing activity is not associated with trading strategies that on average provide any added value to investors even before accounting for expenses. We find that neither liquidity costs nor momentum trading can explain these findings.

1 Introduction

We define window dressing as any attempt of a fund manager to adjust his portfolio immediately before disclosing to the public in order to look more attractive to the investor. This deceptive practice makes the manager's selection ability or style consistency appear better than it actually was. When evaluating

*We thank Annette Larson, Paul Kaplan, Robert Korajczyk, Robert McDonald, Todd Pulvino, and participants at the Zell Center seminar for their comments and suggestions. We would especially like to thank Ravi Jagannathan for all his suggestions and the many insightful discussions. We thank Morningstar, Inc. for providing us with the mutual fund data.

the performance of a fund the investor compares the risk and return tradeoff. If the investment in a particular fund is part of an asset allocation strategy, the individual investor or plan sponsor has to ensure that the fund complies with its investment style. Given the difficulty of characterizing the performance and style of a fund based on past returns, investors may incorporate information on fund holdings. The U.S. Securities and Exchange Commission (SEC) requires funds to report their portfolio holdings to the shareholders at least semi-annually but most funds voluntarily disclose their portfolio holdings every quarter.[1] Some funds provide limited information on their top holdings on a more frequent basis, but fund managers never reveal when the assets were acquired or sold.[2]

Knowing that investors pay attention to disclosed holdings fund managers may be tempted to engage in window dressing. The reasons are manifold:

(i) A fund manager can load up on recently successful stocks such that these winners show up in the top 10 or top 25 holdings. The top holdings are a key part of mutual fund profiles published by prominent mutual fund information resources like Morningstar or Lipper. The financial press tends to pay a disproportionate amount of attention to these top holdings, considering that the top 10 holdings on average constitute only 30% of the total portfolio.

(ii) Managers attempt to hide the fact that they held extremely poorly performing stocks by removing such "embarrassing" stocks from their books before reporting.

(iii) A manager may be tempted to window dress if he missed out on an important stock within his universe. For example, a tech fund manager who did not have a stake in Dell during 1998, when the stock rose by 250% over the year.

(iv) Managers can hide the fact that they picked stocks outside their core investment universe by eliminating such positions prior to the reporting date to seemingly comply with the stated fund objective. An equity fund, for example, might hold a large cash position in a down market and switch back into stocks just before reporting.

(v) The manager shifts portfolio positions into less risky securities. The Sharpe ratio of the reported portfolio then appears more favorable to the investor.

[1] The Rules adopted under the Investment Company Act of 1940 requires funds to transmit a record of the holdings to shareholders at least semi-annually [Rule 30e-1(a)], and within 60 days after the end of the reporting period [Rule 30e-1(c)]. The Securities Act of 1933 requires that funds provide a prospectus. For details see University of Cincinnati, Center for Corporate Law, "Securities Lawyer's Deskbook": www.law.uc.edu/CCL/.

[2] Fidelity e.g. updates the top 10 holdings for all of its funds quarterly and the sector weightings and asset allocation monthly. Vanguard provides both information on a monthly basis. Few funds even went one step further: The San Francisco based Metamarkets.com with its open-disclosure fund OpenFund reported all transactions after completion. Metamarkets closed in July 2001, two years after inception.

The financial press often attributes end-of-quarter stock price movements to window dressing activity by equity mutual funds.[3] While the academic literature has long recognized its existence, e.g. Haugen and Lakonishok (1988) or Lakonishok, Shleifer, Thaler and Vishny (1991), there has been little empirical evidence provided thus far. Lakonishok, Shleifer, Thaler and Vishny (1991) analyze pension fund managers, while Musto (1999) performs a test of window dressing of money market funds. From the analysis of weekly portfolio statistics of these money funds he concludes that fund managers hold fewer private issues and more lower-risk government bonds around the reporting date. Sias and Starks (1997) examine the trading activity of individual and institutional investors at the year end and find that institutions are more inclined to buy recent winners, which is consistent with the window dressing hypothesis.[4]

This paper proposes two methodologies to identify window dressing activity: One to identify funds that window dress their returns [along the arguments (i)-(iii) listed above], and another to detect hiding of style risk [(iv) and (v)]. In both cases the identification is based on a comparison of the realized fund return with the hypothetical return of a buy-and-hold strategy of the reported portfolio. On a daily basis, we calculate the hypothetical return the fund would have earned if it held the reported portfolio already during the weeks leading up to the reporting date. Contrasting this hypothetical return with the realized, pre-expense NAV return reveals information about whether a fund adjusts its positions just before disclosure to look better – i.e. whether the fund does window dressing.

The first measure examines to what extent funds shift into securities with higher recent past returns. In such cases, we expect to see a substantial overperformance of the hypothetical holdings-based returns when compared to the realized NAV returns. Given that trading due to window dressing occurs over the last days at the quarter end, we expect the return difference to drop sharply before reporting. Based on a log-likelihood ratio test with a significance level of 5%, we find that a substantial fraction of 15% of the funds engage in return window dressing. The turnover generated by this trading activity does on average not pay off after the reporting date. The funds identified as return window dressers are typically growth funds with high turnover, high expense ratios, and a poor recent performance.

To capture style hiding we provide an alternative measure that compares the hypothetical returns of the buy-and-hold strategy and the NAV returns with the daily returns on the style benchmark. If the style of the reported portfolio is different from the style of the portfolio held throughout the quarter,

[3] An example is the following extract from the *Wall Street Journal*, "Dow Advances 67.16; Index Shows Gains As the Quarter Ends", September 30, 2003: "[...] Traders attributed a good part of the day's stock gain to 'window dressing' – an effort by money managers to make their portfolios look more attractive before closing them out for the quarter. Managers with too much uninvested cash feel the need to invest it now. They were buying some of the quarter's biggest winners [...]."

[4] Ritter (1988) and Dyl and Maberly (1992) also investigate the "turn-of-the-year" effect, and Brown, Harlow and Starks (1996) analyze fund activity to manipulate risk.

then we expect a discrepancy between the R-squares of the style benchmark with each of these returns. We identify 12% of the fund portfolios where the hypothetical holdings-based returns track the style benchmark substantially closer than the NAV returns. Funds with more assets under management and a larger number of stocks in the reported portfolio are less likely to engage in this type of window dressing. Again, these window dressed portfolios typically exhibit high turnover and high expense ratios, and also tend to have underperformed over he past quarter. Style hiding does not appear to be linked with a specific investment style.

The analysis is based on a large sample of 4,025 mutual funds investing in U.S. equity with 27,702 filings, and a total market capitalization of $2.1 trillion as of December 2001. To identify window dressers we require that we can match at least 95% of the portfolio holdings with daily return data from CRSP. This reduces the subset to 2,691 funds with 11,033 filings, and a total of 10,607 different securities that are held by these funds. According to the Investment Company Institute (ICI), the net assets held by U.S. domestic equity mutual funds totaled $2.3 trillion on December 31, 2002.[5] With 36.1% of the overall fund industry assets, this is the largest fund category, closely followed by money market funds with 35.5%. We are able to match the holdings of 39.6% of all U.S. domestic equity funds by market capitalization.

We compare our findings with other competing explanations. We find that liquidity costs cannot explain the underperformance of NAVs relative to the reported portfolio. When comparing with NAV returns we add back management fees and asset-based costs for distributing the fund's shares. To control for invisible execution costs, we estimate the price impact of trading in the stocks that the fund holds. Costs due to liquidity are too small to explain the differences in returns before the reporting date. Moreover, if liquidity costs were the prime reason for the diverging return differences, we would expect to see the same pattern after the portfolio date. This is not what we see in the data.

For a classical momentum trader [along the definitions in Jegadeesh and Titman (1993, 2001)] who routinely adds recent winners to his portfolio and sells losers, we show that the past NAV returns would gradually converge to the return calculated on the reported holdings. It is the sharp drop that distinguishes window dressers from classical momentum traders. A Monte Carlo experiment illustrates the distinctions in the patterns between a momentum trader and a window dressers.

The finding is also different from the leaning-for-the-tape argument analyzed by Carhart, Kaniel, Musto and Reed (2003). They find evidence that funds bid up prices of stocks they already hold in their portfolio by aggressively trading in these stocks immediately before the closing of the stock exchange on the last trading day before disclosing their holdings. This is a way to manipulate the performance and

[5] "Mutual Fund Fact Book", *Investment Company Institute* (ICI), May 2003, p.68. The net assets of world equity funds ($358.5 billion) are subtracted from the total for equity funds.

can be done by placing relatively small orders. Over a short period of time, the authors find abnormal returns over the last half hour of the quarter and a reversal on the next trading day. Unless the orders are large and induce major shifts in the portfolio compositions, this behavior would equally affect prices for the reported portfolio as well as the NAV returns. Hence, our identification method is not distorted by this activity. In the unlikely case that the portfolio shifts resulting from this bidding-up of prices is substantial, we would capture the fund as a window dresser.

Regardless of the overall performance of a fund, trading over a short period before reporting will incur immediacy costs. This is against the interests of shareholders and raises questions on the governance of the mutual funds. There is an ongoing debate on whether mutual funds should legally be required to report more frequently. Given that holdings do not necessarily provide more insightful information on the risk and performance of the fund, we conjecture that it would be much more effective, if funds were required to disclose the trading date of, say its top ten acquisitions and sells. The disclosure could be with a delay to avoid that successful funds can be imitated. This would enable the investor to get a better understanding of the selection ability of the fund manager and the risk characteristics and performance of past returns.

2 Data Description

Our data set of U.S. domestic equity, open-end funds covers semi-annual holdings from 1997 to 2002. Almost all funds in our sample report at quarterly frequency, but our database covers only semi-annual filings. For each fund we observe the daily net asset values (NAV) per fund share along with a track record of all distributions. The data is provided by Morningstar, Inc. (hereafter Morningstar). The sample of holdings data contains 27,702 reported portfolios from 4,025 funds. We match each reported stock position with daily return data from the Center for Research in Security Prices (CRSP). All filings where we can match at least 95% of all positions (in terms of market capitalization) form the subset we use to identify window dressers. This cutoff reduces the number of funds to 2,691 and the number of filings to 11,033. The Investment Company Institute (ICI) counts 4,756 equity funds at the end of 2002, which includes world equity funds. The total market capitalization of the funds in our sample is \$1,355 trillion at the end of 2001. This accounts for 39.6% of the U.S. domestic equity fund industry.

To control for invisible trading costs we calculate a measure of price impact using intraday data on trades and quotes from TAQ. The 95% matching criterion assures that we can also assign a liquidity measure for the fund's holdings with a reasonable degree of accuracy. A total of 173 funds with 833 filings in the subset are index funds. The sample also includes 624 dead funds.

2.1 Buy-and-Hold Returns

Any test of window dressing attempts to assess how representative the disclosed portfolios are. In this subsection we describe the return calculation of a buy-and-hold strategy of the reported portfolio. Before the reporting date, we determine the hypothetical return the fund would have earned, if it had held the portfolio it reported at quarter end. These buy-and-hold returns are the benchmark against which we compare the fund's realized returns.

The reporting dates in our sample are the two available filings closest to June 30th and December 31st each year. For the majority of the funds the reporting date is at the end of these two quarters. The portfolio holdings are on the individual fund level and show the complete record of holdings.

For each stock position in the mutual fund portfolio we retrieve daily stock prices from CRSP to create a time series of the portfolio returns starting 182 days before the reporting date and ending 182 days afterwards. We add up the dollar amounts of all cash and cash equivalent positions and calculate the fraction of total fund's net asset values made up of each stock and the combined cash position. These are the portfolio weights. When identifying window dressers all filings for which we can match daily returns for less than 95% of total net assets are excluded from the sample.[6]

Let time $t = 0$ denote the reporting date. The portfolio weights for stock i are then, for any $t = -182, ..., 182$, defined as

$$w_{i,t} = \frac{P_{i,t} n^0_{i,t}}{\sum P_{i,t} n^0_{i,t}} \tag{1}$$

where $P_{i,t}$ is the closing price or the average of the bid and ask price at the end of the trading day, and $n^0_{i,t}$ the adjusted number of shares for stock i relative to date $t = 0$. To account for stock splits, reverse splits, right issues, share buybacks, spin-offs, issuances and offers, we adjust the number of shares at different points in time. The reference point for adjusting the number of shares is always the reporting date. Take a 2-for-1 split as an example and consider the two cases where (i) the stock split occurs before the reporting date, and (ii) after $t = 0$. The adjustment factor is $Q_i = 1$ before and $Q_i = 2$ after the event. In general,

$$n^0_{i,t} = n_{i.t} \frac{Q_{i,0}}{Q_{i,t}}$$

where $n_{i,t}$ denotes the unadjusted number of stocks. In scenario (i) $n_{i,t}$ is adjusted by $Q_{i,t}/Q_{i,0} = 1/2$, and if the stock is split after $t = 0$ the appropriate adjustment is $Q_{i,t}/Q_{i,0} = 2/1$.[7]

The return on the buy-and-hold strategy for a fund, R^P_t, is

[6] Most funds and reportings where less than 95% is matched include Treasury bond, corporate bond, or international stock positions for which wed did not have daily price data.

[7] We use the cumulative factor to adjust number of shares, CFACSHR, from CRSP. Instead of using the differences in adjusted prices we use the holding period returns between two dates.

$$R_t^P = \sum_i w_{i,t} r_{i,t} \tag{2}$$

where $w_{i,t}$ are the portfolio weights as defined in (1) and $r_{i,t}$ are the corresponding holding period returns.

We assign a return of zero to cash and cash equivalent positions. This underestimates the return on the buy-and-hold strategy and reduces the underperformance of returns on window dressed portfolios that we expect to see before disclosing the holdings. Stock positions that we cannot match with a daily return series are also assumed to have zero return. On average, this will likely underestimate the return of the buy-and-hold strategy as well. An alternative would be to assign the average return of the rest of the holdings as the return of the unmatched position. To ascertain whether our 95% requirement for the fraction of matching positions does not introduce any systematic bias we recalculated all the main results with the subset of fund portfolios with 100% matching positions and did not detect any qualitative differences.

2.2 Fund Characteristics and Investment Style

Fund characteristics such as the expense ratio, turnover, investment style, rating, etc., are available at annual frequency. Missing values for fund characteristics, in particular expense and turnover ratios, were complemented with data from the CRSP Survivorship-Bias Free US Mutual Fund Database (MFDB). Using intraday trades and quotes on the underlying individual stocks from the Trade and Quote database (TAQ) we assign a liquidity measure to each reported portfolio as the weighted average of the liquidities of the individual stocks in the portfolio.

2.2.1 Fund Styles

Funds are classified into nine investment styles along the two dimensions value-growth and large-small cap. We use Morningstar's assignments to the nine quadrants of the style box.[8] The three size classes on the vertical axis are large, medium and small cap. Morningstar defines large stocks as the group of stocks with the largest market capitalization that contributes 70% to the total market capitalization of all publicly traded, domestic stocks. The next 20% are medium size stocks and the remaining 10% small-cap stocks. The geometric mean of all stocks held by the fund determines its position on the vertical axis.[9]

[8] The style box was introduced by Sharpe (1988) and Tierney and Winston (1991).

[9] Suppose the fund holds three stocks A, B and C with weights 60%, 30% and 10% with market capitalizations of 100, 10 and 1,000 million. The geometric mean is then $(100^{0.6}) \times (10^{0.3}) \times (1000^{0.1}) = 125.90$, which is larger than the median market capitalization, but below the mean of 263.00.

The horizontal axis of the style box is split into the categories value, blend, and growth. On the individual stock level, Morningstar calculates a value and growth score based on historical and prospective stock characteristics. The historical and forward-looking data each contribute 50% to the scores. The historical data components for the value score are price-to-book, price-to-sales, price-to-cash flow and dividend yield; each with equal weight. Growth score components are historical earnings growth, sales growth, cash flow growth, and book-to-value growth. The market capitalization weighted value/growth score of the individual positions determines the fund style. An alternative would be to classify funds using Sharpe's (1988, 1992) style regressions.[10]

2.2.2 The Subsample Used to Identify Window Dressers

Panel (a) in Figure 1 summarizes the fraction of all portfolio positions that can be matched with daily returns from CRSP for all 27,702 filings from 4,025 funds. To be included in the sample we use to identify window dressers at least 95% (market capitalization weighted) of the positions must match. The cutoff at 95% is indicated by the solid, vertical line. Panel (b) describes the number of filings per fund for the subset of 2,691 funds (and 11,033 reported portfolios) where we can assign daily returns for at least 95% of the net assets. At most, there are eleven semi-annual filings between June 1997 and June 2002. For 1,002 funds 5-11 filings are observed, which in total account for 65.0% of the reportings used to identify window dressers. For 1,953 filings the full set of the reported securities can be linked with a daily returns. On average the sample contains 4.2 filings per fund.

Table 1 compares the number of funds and the market capitalization of the subset of 2,691 funds with 95% matching positions to the full sample of 4,025 U.S. domestic equity funds. The table illustrates that the sample of these selected funds accounts for a representative number of all U.S. equity funds within each of the nine Morningstar style orientations.

2.2.3 Fund Characteristics Vary with Style

Table 2 breaks the average fund characteristics down by style. The list covers the characteristics that we consider to be potentially significantly different between window dressers and non-window dressers (see section 3.7). Mornigstar rates funds from five stars to one star based on past performance. Risk-adjusted fund returns are evaluated relative to peers within the same investment style.[11] A pre-specified fraction of all funds receive five to one stars: The top 10% get five stars, the next 22.5% four, the middle

[10] For a detailed description of the Morningstar style box classification see www.morningstar.com, "Mutual Funds", help function for "Style Box".

[11] Morningstar enhanced the rating system in July 2002. The new method uses a refined grid of peer groups and an adapted risk-adjustment to put more emphasis on downward variation ["Fact Sheet: The New Morningstar Rating for Funds", www.morningstar.com, 2002]

35% three, 22.5% two, and the bottom 10% one. Funds in existence for less than three years are not rated (rating 0).

Index funds with a large number of stocks explain the discrepancy between the arithmetic average number of stocks and the median values. The broadest fund in our sample, the Fidelity Spartan Extended Market Index (ticker FSEMX) held 3,468 stock in June of 2001 and is a member of the medium blend category. Giants like the Vanguard 500 Index fund (65.9 billion in December 2002) and the biggest actively managed fund, Fidelity Magellan (62.5 billions), dominate the average market capitalization of large blend funds. Cash holdings do not differ systematically across investment styles. The liquidity costs are measured by the estimated price impact in basis points when $1 million shares are traded over a half hour period. Average turnover ratios and expense ratios are larger for growth funds.

The distributions of these characteristics are shown in Figure 2. In Panel (a), S&P 500 index funds are the main reason for the second mode to the right in the distribution of number of stocks in the portfolio [log10(500) = 2.7]. A total of 464 filings list between 490 and 510 different equity positions.[12] It is interesting to note that for equity funds 5% cash seems to be a critical threshold [Panel (c)]. Only 5.7% of all funds report positions in cash or cash equivalent securities beyond 5% of total net assets. The average fraction of total net assets that is invested in the top 10 holdings is 28.8% [Panel (d)]. The left tales in the distributions of expense ratio and annual turnover [Panels (e) and (f)] are again mainly due to index funds. A large fraction (40.8%) of the filings is from funds which are not rated by Morningstar [Panel (g)].

3 Methodology to Identify Return Window Dressers

In this section we introduce a new methodology to identify portfolios that are window dressed with respect to the recent return of the reported holdings. A fund manager may be tempted to report securities with a relatively high recent return to convey superior stock picking ability to the investor. Prior to disclosure, a window dresser would replace stocks with a poor recent return with stocks that performed well. The return characteristics for the disclosed securities are then no longer representative of what the fund actually held throughout the quarter.

First, we investigate the net changes in portfolio positions between subsequent semi-annual filings. Some funds exhibit a high buying intensity of top quarter performers, others sell off large fractions of quarter losers. The comparison of subsequent reported portfolios, however, does not reveal any

[12] These filings are reported by 98 different funds, of which 76 have the word "Index" in its name. In 32 cases the name contains explicitly "S&P 500 Index".

information about the timing of these transactions. Moreover, a window dresser does not necessarily have to sell the bottom performers or add stellar stocks. Instead, he could exchange large positions with stocks that had an only slightly better past performance. If buying winners and selling losers is due to window dressing, the trading activity involving these securities occurs over the last days of the quarter. The proposed shape test captures the typical return pattern between the hypothetical holdings-based returns and the realized NAV returns we expect from a window dresser.

3.1 What to Expect From a Return Window Dresser

For a manager who buys recently successful stocks and removes losers from his portfolio just before disclosure, the buy-and-hold strategy of the ex-post reported portfolio will outperform the NAV returns over the weeks prior to the reporting date. A key feature that distinguishes such a window dresser from a momentum trader is that the portfolio and NAV differ substantially even during the last days before reporting. A momentum trader adds recently successful stocks on an ongoing basis and, hence, also reports recently successful stocks. However, we would not expect that the trading activity into recent winners and out of losers occurs mainly before reporting dates. Furthermore, for a successful momentum trader we would expect the NAVs to outperform a simple buy-and-hold strategy of the disclosed portfolio after the reporting date. This need not to be the case for an unsuccessful momentum trader who might even underperform due to the execution costs he incurs.

For return window dressing we expect to observe one of the following patterns, or a combination of these:

(i) Prior to the reporting date, the realized NAVs underperform the hypothetical returns on the ex-post reported portfolio (buy-and-hold returns).

(ii) The manager buys recently strong stocks and/or to sell losers in his portfolio.

(iii) The fund has at least medium, but more likely high turnover.

(iv) The manager routinely adjusts the fund portfolio in a significant way just before disclosure.

The following stylized example illustrates the magnitudes we would expect from this trading activity. Assume the fund holds total net assets worth \$10 million. At the beginning of the quarter, the fund holds a position in stock A that accounts for 2% of total net assets. The position in stock A suffers a 25% loss over the quarter, whereas the rest of the portfolio earns 10%. Stock B that the fund did not hold yields a return of +25% over the same quarter. Just before reporting, the managers sells A and buys B.

	NAV Return				Buy-and-Hold Return			
	Beginning of Quarter		End of Quarter		Reported Portfolio		Initial Portfolio	
	Weight	Value	Weight	Value	Weight	Value	Weight	Value
Stock A	2.00%	200,000	1.26%	150,000				
Stock B					1.26%	150,000	1.21%	120,000
Rest	98.00%	9,800,000	98.74%	10,780,000	98.74%	10,780,000	98.79%	9,800,000
Total		10,000,000		10,930,000		10,930,000		9,920,000

The total holding period NAV return (before subtracting any expenses) for an investor would be $0.98 \times 10\% + 0.02 \times (-25\%) = 9.30\%$. Assume the manager of the fund decides to window dress and exchange the position in stock A with stock B. At the end of the quarter the value of the position in stock A dropped to \$150,000. When the fund reports a position of \$150,000 in stock B we would calculate the hypothetical return on the buy-and-hold portfolio. If the fund held the position in B over the whole quarter, then its initial investment in B must have been \$120,000 (that then increased by 25%). At the beginning of the quarter, stock B would have constituted 120,000/(120,000+9,800,000)=1.21% of the portfolio. The return of the buy-and-hold strategy of the reported portfolio is $0.12 \times 25\% + 0.988 \times 10\% = 10.18\%$. The observed difference between the holdings-based and NAV return is $10.18\% - 9.30\% = 0.88\%$ and dividing by 90 days per quarter we get 0.98 basis points per day. To look better by one basis point a day the fund manager needs to substitute 1.43% of daily average net assets over the quarter.[13] His turnover in percent per annum hence increases by 5.72% due to this window dressing activity.

3.2 Calculating the Pre-Expense NAV Return

To assess the performance of a funds we need to determine the total holding period return. This requires to take into account distributions and share splits. By investing in a fund the investor benefits from professional management of the portfolio. Independent of the success of the trading activity the fund provides services such as collecting dividends, reinvestment of those proceeds, keeping track records of shareholders, produce reports on performance, etc. The financial adviser who manages the fund and any affiliated service providers are compensated through management fees and service fees. To allow a fair comparison with a buy-and-hold strategy we add back these operating expenses to determine the fund's pre-expense performance. Fees that are not paid out of the fund's assets but are rather directly paid by the investor do not affect this adjustment.

[13] Turnover is the quotient of traded assets and average (daily) net assets: $150,000/(0.5 \times 10,000,000 + 0.5 \times 10,930,000) = 1.43\%$.

3.2.1 Net Asset Value

The net asset value (NAV) of a mutual fund is the value of the underlying assets minus its liabilities. Dividing by the number of mutual fund shares outstanding returns the dollar value of single share, or per share NAV. Mutual funds, legally known as open-end funds, differ from closed-end funds and Unit Investment Trusts (UIT) in that the investor directly buys the shares from the fund and not through a secondary market. Shares can be redeemed at the net asset value (NAV) on a daily basis.[14] Mutual fund shares are sold on a continuous basis unless a fund becomes too large and closes to new investors – like Fidelity Magellan in September 1997.[15]

To buy a share of the fund the investor pays the per share NAV plus any fees that the fund imposes at purchase. Depending on share class, fee structure of the fund, and the policy of the fund family, these fees are sales loads or purchase fees. When investors redeem shares of an open-end mutual fund, they sell them back to the fund. The investor receives the per share NAV minus any fees, if applicable. The fees consist of deferred sales loads and/or redemption fees.

The calculation of NAVs is regulated under the Investment Company Act of 1940 and the Rules and Regulations promulgated under that Act. Most open-end funds chose to be listed on Nasdaq and to qualify for listing, the fund is subject to the National Association of Security Dealers (NASD) rules and regulations. Under these regulations assets have to be valued at the closing prices of the major U.S. exchanges (4:00pm ET on a regular trading day) and the NAV must be reported to Nasdaq no later than 5:55pm.

3.2.2 Adjusting NAVs for Dividends and Capital Gains

Distributions and expenses are accrued to date for purposes of the NAV calculation. There are two types of distributions: dividends and capital gains. Mutual funds are required by law to pay virtually all gains to their shareholders.[16] For tax purposes short-term capital gains are reported separately to investors. Short-term capital gains are realized when the fund sells an asset it has owned for twelve months or less, otherwise the capital gain distribution is classified as a long-term capital gain. Long-term capital gains are generally taxed at favorable rates, whereas short-term capital gains and dividends must be reported as ordinary income.[17] The time the fund holds a stock determines whether it is a short- or

[14] Closed-end fund shares are typically not redeemable to the fund itself, but are traded on an exchange like a stock.

[15] Fidelity Magellan closed on September 30, 1997, to new investors outside the Fidelity retirement plans ["Trimming its sails: Magellan, the flagship of Fidelity, will close to most new investors", *The Wall Street Journal*, August 27, 1997]. At that time, the fund was the world's largest fund with $62.9 billion assets and more than 4 million shareholders.

[16] Subchapter M of the Internal Revenue Code of 1986. Originally established under the Revenue Act of 1936.

[17] "Mutual Fund Fact Book", *ICI*, May 2003, p.19: Beginning of 2001 capital gains on assets held for more than 5 years are eligible for treatment as "qualified five-year gains" and taxed at a lower rate.

long-term capital gain, and not the length of the time period the investor holds the mutual fund share.

First, we determine the total return to the investor net of operating expenses and fees. This requires to add back all the distributions and adjust for stock splits. The daily return, adjusted for distributions and stock splits is calculated as

$$R^*_{t-1,t} = \frac{NAV_t + D_t}{NAV_{t-1}} SR_t - 1 \tag{3}$$

where NAV_t is the net asset value at the closing of the current trading day, NAV_{t-1} the net asset value at the end of the previous exchange day, D_t is the sum of dividends and capital gains distributions (if any) that are reinvested at NAV_t. In case of share splits, the fraction SR_t describes the split ratio, the number of new shares per number of old shares. Distributions are usually paid on a quarterly basis. They include dividends and capital gains net of management fees. Most funds give the investor the choice of whether the distribution should be paid out or reinvested. Reinvestments are usually exempt from any front-end sales load. Expression (3) is therefore the appropriate return under the assumption that all distributions are reinvested.

3.2.3 Adding Back Operating Expenses

The expense ratio expresses the percentage of funds assets paid for operating expenses. The expense ratio accounts for management fees to the investment adviser, 12b-1 fees, and other operating expenses; such as accounting, custodial, and legal expenses, or costs of shareholder mailings. Not included are transaction costs in the form of brokerage fees. All costs for distribution services other than 12b-1 fees – front-end, deferred sales, back-end loads, maintenance fees, and redemption charges – are not part of the expense ratio since they are not paid out of the assets of the fund.[18]

Operating expenses may vary across the different fund share classes. A majority of 55% of all funds today are multi-class funds [see Reid and Rea (2003)]. Our database contains the information on the major share class with the earliest inception date – which is usually called share class A.[19] The expense ratio is recorded annually. Adjusting for the dividends and capital gains for the given share class, and adding back the operating expenses yields the same pre-expense NAV return as each share class is part of the same underlying portfolio. The holding period return from the perspective of the investor differs based on the distribution fees of the individual share classes and his investment horizon.

The total expense ratio is defined as the sum of all operating expenses over the period divided by the average daily net assets. Total expenses for an investment of A are:

[18] These loads and fees are collected by the fund distributor, which compensates the broker or transfer agent. Depending on the share class, the investor pays the distribution costs through loads or 12b-1 fees, or a combination of the two.

[19] The Rule 18f-3 under the Investment Company Act of 1940 that allows a fund to have multiple fund share classes was adopted in 1995. The law does not specify the naming of share classes.

$$A\sum_{t=1}^{N}(1-E_{daily})^{t-1}(1+r_{daily})^{t}E_{daily}$$

The average net asset value over the N days then equals

$$\frac{A}{N}\sum_{t=1}^{N}(1-E_{daily})^{t}(1+r_{daily})^{t}$$

From this we get the annual expense ratio as:

$$E_{annual}=\frac{A\times E_{daily}}{\frac{A}{N}(1-E_{daily})}$$

Typically, annual expense ratios are in the range from 1-1.5% p.a. Solving for E_{daily} and given that there are approximately 250 trading days per year

$$E_{daily}=\frac{E_{annual}}{N+E_{annual}}\approx\frac{E_{annual}}{250+E_{annual}} \tag{4}$$

We use this approximation for the daily expenses to compute the pre-expense fund return. The details are described in O'Neal (1999).

$$R_t^{NAV}=\frac{1+R_t^*}{1-E_{daily}}-1 \tag{5}$$

Since beginning of 2002, the SEC requires funds to report after-tax returns for investment horizons of one, five and ten years, including and excluding costs of redemption in a standardized format.

3.3 Difference Between Holdings-Based and NAV Returns

Figure 3 shows the pattern of return differences averaged over all 2,691 funds and 11,033 filings where we can match daily returns for at least 95% of the holdings. The return difference is defined as the return on the buy-and-hold strategy minus the realized NAV return, $R_t^P-R_t^{NAV}$. When the hypothetical returns on the portfolio that is reported at the end of the quarter outperform the fund's realized returns, the difference is positive. Going backward and forward in time, starting from the reporting date, we cannot detect any distinct asymmetry around the reporting date. As is to be expected the dispersion increases the farther away we move from the reporting date. The median average return difference over the weekly intervals stays close to zero. Also the interquartile range, indicated by the gray boxes, is rather tight and increases from 3.5 to 10.8 basis points after 13 weeks, and 11.2 basis points 13 weeks prior to reporting. The T-bars indicate the range with 95% of all observation.

The distributions of these return differences before and after disclosure (Figure 4) exhibit the typical shape that is expected from daily returns: a much higher kurtosis than a bell-shaped Normal distribution. We would expect window dressers to be in the right tail of the distribution prior to reporting. This does not need to be the case for a style rotator. If the fund switches portfolio positions to conceal its true style or risk characteristics, the return on the disclosed portfolio may be similar.

3.4 Do Managers Sell Losers and Add Winners?

The analysis uses the total of 6,490 pairs of reported portfolios for a given fund that lie not more than 190 days apart. The first pairs of observations are June 1997 and December 1997. For all adjacent 6,490 portfolios we determine the fraction of total net assets that has been shifted into (out of) recently strong (weak) performing stocks. The fractions are calculated according to equation (1), i.e. the same stock price is used for two adjacent portfolios to ensure that we capture only active net trades over the quarter.

Given that stated fund objectives and investment strategies most often focus on a particular style, either a stock size class and/or value-growth orientation, we define quarter winners and losers within each style category separately. The subsection below describes our approach to determine the style universes. The top and bottom 10% of the stocks ranked by performance are then classified as winners and losers. By looking at the performance over the past three months before the reporting date our time horizon is also different from what is typically considered in the momentum literature.

3.4.1 Classifying Stocks as Winners and Losers Within Style Categories

A window dresser adds recently successful securities to his portfolio and/or sells "embarrassing" stocks. Most likely a fund manager switches into stocks that performed well over the time since the last reporting. For most funds the time span between two disclosures is a quarter. However, as many fund evaluations and analyst's reports focus on top 10 or 25 holdings, a fund manager may not only be tempted to add the quarter's top performers, but also holding just recently stellar stocks is attractive to mimic selection skill. A "disaster" stock over the very last weeks before reporting might as well be eliminated from the portfolio. Moreover, depending on the universe of stocks the fund invests into the relevant best or worst performing stocks are different. We determine each month and for each of the nine style universes the top and bottom 10% performing stocks over the three months before reporting. This involves two steps: (i) Determining the style universes, and (ii) ranking the stocks within a specific style universe and a given time horizon.

We determine the core universe of stocks that is held by funds within each of the nine style box quadrants by counting how often a stock shows up in the holdings of all funds with a particular style

orientation. We do not consider market capitalization weighted holdings to prevent a few very large funds from dominating the selection of the universe. This assumes that it is a stronger indicator for a stock being held by ten small funds within the same style than by one fund with ten times the market capitalization. The final universes include the 50% most frequently held stocks. The nine stock universes are recalculated each year. A more standard approach would be to determine fundamental stock characteristics. The main problem with this approach being that only about two thirds of stocks can be classified when matching book-to-market values from COMPUSTAT. With our approach some borderline cases may also fall within more than one style universes.

Each month we determine the return over the previous month, the preceding two and three months (quarter). A stock by our definition qualifies as a relatively strong stock relative to its peers if within the universe it has been a top 10% performer over a given month. The same approach is used to select the relatively weak stocks. We use the terms relatively strong and weak stocks to highlight the difference from the typical definition in the literature on momentum trading. The time horizon for momentum strategies is typically longer and stocks are not classified as winners and losers within specific investment styles.

The correlation matrix in table 3 compares recently strong and weak stocks over the three time horizons one, two, and three months. We argued in the introduction to this section, that a fund manager who contemplates exchanging stock positions to look better at the quarter end does not necessarily focus on the performance over the entire past quarter. However, the correlations illustrate that the definition of winners for the overlapping time horizons are highly correlated, somewhat more for strong stocks. For what follows we define strong and weak stocks over the three month horizon.

3.4.2 Net Changes in Portfolio Positions

We consider buying of winners and selling of losers separately since they do not need to coincide. A fund loading up on recently stellar performers to move them up into the top ranks does not necessarily remove overall losers from the portfolio. The fund may use uninvested cash, income from dividends, or net money inflows into the fund to increase the weight on successful securities. Vice versa, an "embarrassing" stock need not be replaced by a quarter winner.

For each fund the percentage of the net asset value that has been invested in quarter winners between two reporting dates is calculated. Since we do not observe offsetting trades within the quarter these percentages represent net changes. We divide this percentage by the overall net turnover between the filings to determine a ratio of buying intensity of recently strong stocks. When the trading activity in these well performing stocks is comparable to the overall turnover of the funds we would expect a distribution around 10% – the top 10% performing stocks are defined as recently strong stocks. Panel

(a) in Figure 5 shows that a substantial number of the funds (1893) in the sample have ratios greater than one. A similar comparison is provided for selling weak stocks. As we defined relatively weak stocks as the bottom performers for a given style, a fund may not have any of these "embarrassing" stocks in the portfolio. In fact, Panel (b) illustrates that 2037 reported portfolios do not contain a position in an "embarrassing" stock and on average funds have a position of 2.2% in these stocks. The distribution of the ratios measuring the percentage of relatively weak stocks in the portfolio divided by the net turnover also has a fat right tail with a mean of 1.6 and 60.4% of all funds with ratios higher than one [Panel (c)]. Funds holding less than 0.25% embarassing stocks are excluded.

Alternatively, we consider losers within the fund's own disclosed portfolio, defined as stocks with a return that is at least one standard deviation below the mean return of the fund. The results are shown in Panels (d) and (e). On average, funds hold 8.7% portfolio losers and they tend to sell off losers more often than other securities in the portfolio until the next semi-annual filing. The mean is 1.3 and 64.5% of the portfolios with at least 0.25% losers have ratios above one.

3.5 Shape Test to Identify Window Dressing

Our identification method compares realized net asset value returns of fund portfolio i, $R_{i,t}^{NAV}$, and compares these with the hypothetical return of a buy-and-hold strategy of the portfolio that is reported at $t = 0$, $R_{i,t}^{P}$. For a given reported fund portfolio we take the reporting date as $t = 0$ and look at the 13 weeks before and after the reporting date, $w = -13, ..., 0, ...13$. For each fund portfolio, $i = 1, ..., N$, and each week, w, we calculate the difference between the average daily return on the buy-and-hold strategy and the realized NAV returns $\overline{R}_{i,w}^{P} - \overline{R}_{i,w}^{NAV}$, as in Figure 3 above. The average is determined as the geometric mean return in basis points per day.

In a first step we estimate the distribution of the weekly return differences. The second step consists of a log likelihood ratio test to see whether the weekly return differences prior to the reporting date follow the pattern we would expect from a window dressed portfolio.

Under the null hypothesis of no window dressing we make the following assumptions:

(i) The distribution of weekly return differences, $\overline{R}_{i,w}^{P} - \overline{R}_{i,w}^{NAV}$, can be approximated by a Generalized Error Distribution (GED). Daily return differences are not normally distributed. Therefore we use the GED that is widely used in the GARCH literature. This distributions allows to fit the leptokurtic shape of the distribution better.

(ii) The shape of the distribution changes when moving away from the reporting date. However, going backward or forward in time should exhibit the same changes in the distribution. Thus we assume that the change in the distributions is symmetric around the reporting date.

(iii) Weekly return differences are independent over time.

First, we fit a GED distribution to the return differences for each of the weeks after the reporting date, $w = 1, ..., 13$. For each week this results in a set of parameters η_w and σ_w, where σ_w is a scale parameter and η governs the thickness of the tails in the distribution.

$$(\eta_w, \sigma_w) = \arg\max_{\sigma,\eta} \sum_{i=1}^{N} \log f\left(\overline{R}_{i,w}^{P} - \overline{R}_{i,w}^{NAV} \mid \eta_w, \sigma_w\right)$$

where $f(.)$

$$\begin{aligned} \log f(x, \eta, \sigma) &= N\left\{\ln\left(\frac{\eta}{\lambda}\right) - \left(1 + \eta^{-1}\right)\ln(2) - \ln\left[\Gamma\left(\eta^{-1}\right)\right]\right\} \\ &\quad -0.5\sum_{i=1}^{N}\left|\frac{x}{\lambda\sigma^{-1}}\right|^{\eta} - 0.5\sum_{i=1}^{N}\ln(\sigma) \end{aligned}$$

with the gamma function $\Gamma(.)$ and

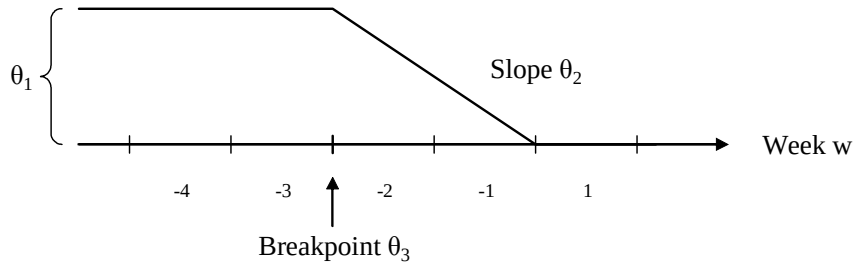
$$\lambda = \left[\frac{2^{-2/\eta}\Gamma(1/\eta)}{\Gamma(3/\eta)}\right]^{0.5}$$

By the assumption (ii) of symmetry around the reporting date we assume that the parameters for, say the second week after the reporting date, are equal to the parameters two weeks prior to the reporting date. Based on the symmetry assumption this is the case for all 13 weeks prior to the reporting date, $\eta_{-w} = \eta_w$ and $\sigma_{-w} = \sigma_w$.

For a fund manager who window dresses the portfolio return we expect a positive return difference before the reporting date that decreases immediately before the reporting date. Under the alternative hypothesis of window dressing we therefore postulate the following pattern for the return difference prior to the reporting date:

$$y_{i,t} = \overline{R}_{i,w}^{P} - \overline{R}_{i,w}^{NAV} - \left[\theta_{i,1} - \theta_{i,2}\left(w - \theta_{i,3}\right)1_{\{w>\theta_{i,3}\}}\right]$$

This expected shape corresponding to the equation is illustrated below.



Over the weeks leading up to the reporting date the average return difference is initially θ_1. After the breakpoint at θ_3 the return difference decreases with slope θ_2. We allow the breakpoint θ_3 to be in one of the weeks over the last month, i.e. $\theta_3 \in \{-4, -3, -2\}$. The indicator function $1_{\{w>\theta_{i,3}\}}$ is one for the weeks after θ_3. If we take $\theta_3 = -3$ as an example, the return difference will become $\theta_1 - \theta_2$ two weeks before the reporting date and $\theta_1 - 2\theta_2$ over the last week. The parameter values for the test can be summarized as follows:

H_0: No window dressing, $\theta_1 = \theta_2 = \theta_3 = 0$.

H_A: Window dressing, $\theta_1 > 0$, $\theta_2 \leqslant 0$ and $\theta_3 \in \{-4, -3, -2\}$.

Combined with the assumptions above, the log likelihood function below is maximized under the null hypothesis and the alternative hypothesis for each fund and each week prior to the reporting date.

$$\max \sum_{w=-1}^{-13} \log f \left\{ \overline{R}_{i,w}^{P} - \overline{R}_{i,w}^{NAV} - \left[\theta_{i,1} - \theta_{i,2} \left(w - \theta_{i,3} \right) 1_{\{w>\theta_{i,3}\}} \right] \mid \eta_{i,-w}, \sigma_{i,-w} \right\}$$

The log-likelihood ratio test of H_0 against H_A is asymptotically chi-squared distributed with three degrees of freedom. We identify 1,474 portfolios (15.6%), where H_0 is rejected at a 5% significance level, as window dressed.

3.6 Average Return Differences for Window Dressers

To illustrate the scale of the return differences generated by window dressing we repeat the boxplot from section 3.3 for the 1,474 return window dressed (WD) portfolios. We document that after the reporting date the return differences of WD portfolios are again centered around zero with dispersion gradually increasing. We also find that return window dressing is not a year-end phenomenon. The comparison with funds that are identified as actively trading in winners and losers by insption of net changes in portfolio holdings (section 3.4) reveals that these funds do not exhibit the distinct behavior of the WDs from our shape test. Only for fund portfolios that added quarter winners between two filings the NAV returns systematically underperform the hypothetical buy-and-hold returns.

3.6.1 Not a Year-End Effect

Figure 6 shows the return differences between the returns on a buy-and-hold strategy of the reported portfolio and the realized NAV returns for non-overlapping, weekly intervals before and after the reporting date, $\overline{R}_{w}^{P} - \overline{R}_{w}^{NAV}$. The gray shaded boxes measure the 25th and 75th percentile, and the line drawn across the median. Compared to Figure 3 the T-bars indicating the range where 95% of the observations fall into are dropped. Panel (b) describes the subset of 1,474 portfolios that are identified as window dressed according to the shape test. The median return difference is approximately 5 basis

points per day during the past quarter. By construction the gap closes over the last three weeks leading up to the reporting date.

However, the weekly intervals are non-overlapping periods and it is not a priori given that geometric mean return differences would on average remain positive each week. The drop in these return differences over the last week is substantial and the interquartile range for all 1,474 portfolios is clearly shifted upwards. Most strikingly, there is no evident pattern after the reporting date. On average, there no longer seem to be any systematic deviations from zero. Simply holding the reported portfolio over the next quarter (13 weeks) would on average yield the same return. This comparison is based on NAV returns before operating expenses are deducted. Panel (a) contains the return differences for the subset of the remaining set of 9,559 funds that are not classified as window dressers. The return differences for these funds still show a symmetric pattern around the reporting date. Medians are close to zero and the dispersion increases the further away the weeks are from the reporting date.

Panels (c) and (d) break the 1,474 WD portfolios down into two subsets; one with all 603 WD portfolios in December and another with 871 WD portfolios with reporting dates other than December. Most WD portfolios reported throughout the year are in June (523), March (109) and September (44). The comparable number of filings as well as the patterns of the return differences rule out the hypothesis that the window dressing activity is primarily driven by tax-loss sellers. This is consistent with the findings of Sias and Starks (1997). The authors conclude that selling losers due to tax effects at the year end is explained largely by transactions of individual investors.

3.6.2 Comparisons of Net Holdings Changes May Not be Able to Detect Window Dressing

In section 3.4, we analyzed changes in holdings between adjacent filings. The question is how fund managers who added winners or sold losers compare to the funds we identify as window dressers based on the shape test. For this purpose we inspect the top decile of buyers of relatively strong stocks, sellers of relatively weak stocks within its style, and sellers of losers within their portfolio. All three measures of holdings changes were divided by the overall net turnover to get a measure of the relative trading intensity in these stocks. Thus, we compare the right tails in the distributions in the second column of Figure 5.

The two graphs in the top row of Figure 7 show the median of the weekly return differences for the 1,474 return WD portfolios from the shape test. A separate line is fitted through the medians for both 13-week periods by least squares. Panels (b) and (c) displays the return difference for the 649 portfolios that were among the top 10% buyers of recently strong stocks over the quarter preceding the reporting date (weeks -13 to -1). Panels (e) and (f) show the same diagram for the 649 top 10% sellers of recently

weak stocks. The pattern for selling weak stocks is less clear. What remains is the conclusion that going forward in time the trading activity does not add any value vis-à-vis the benchmark of a buy-and-hold strategy of the reported portfolio – even before accounting for expenses. As above, the median for the filings that are not classified as WD [Panel (d)] exhibit no systematic deviations from zero.

4 Characteristics of Window Dressers

What characteristics would we expect window dressed portfolios to exhibit? Using the methodology outlined above, we have identified a number of fund filings as likely to have been window dressed based on daily NAVs as well as reported portfolio holdings. This section investigates whether the identified portfolios indeed exhibit the characteristics one would expect from funds engaging in window dressing. Finding that the identified funds on average possess the characteristics that one would expect from a window dresser will help rule out the possibility that they were identified by chance.

To be specific we would expect window dressers to possess some or all of the following properties:

(i) Medium to high turnover. The example in section 3.1 illustrates that the observed window dressing activity alone will easily imply an additional 30% annual turnover.

(ii) Funds with poor past performance are more tempted to window dress. A downside rating revision can induce investors to withdraw capital allocated to the fund. Current rating systems most often incorporate holdings information.

(iii) For funds with a short history, the investor may pay more attention to holdings given the limited return series.

(iv) Investors who wish to see "glamour" stocks in a fund portfolio will be more likely investing in growth stocks. Value investors are considered to be more hard-nosed.

(v) Funds holding liquid stocks may engage more often in window dressing activity as trading in these stocks is less costly.

In the next subsection we first estimate the invisible trading costs for each fund. We apply the approach by Breen, Hodrick and Korajczyk (2002) to determine the price impact of selling a share of the reported portfolio.

4.1 Estimating Invisible Trading Costs

Management fees are part of the expense ratio. This does not fully describe the costs of an active strategy. In particular, invisible transactions costs are not accounted for in any mutual fund report

and may differ substantially across different investment styles. Our target is to estimate the costs of buying or selling $1 million worth of a particular stock. We calculate the liquidity costs of the fund as the market-cap weighted average of the price impacts of the individual stock positions. The liquidity measure captures the expected price effect when the respective underlying fund portfolio is traded.

The basis for the calculation of liquidity costs is the TAQ database, which contains intraday trades and quotes for all securities listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX) and the Nasdaq National Market System and SmallCap issues (Nasdaq). We closely follow the methodology by Breen, Hodrick and Korajczyk (2002) to determine the liquidity measure for each stock held by the mutual funds in our sample. For each stock i we determine a liquidity measure l_i. In the first step, all trades for stock i on a given trading day are associated with the prevailing bid and ask quotes. As recommended by Lee and Ready (1991) and Odders-White (2000) trades are matched with quotes that have been revised at least 5 seconds prior to the time stamp of the recorded trade. If a trade is above (below) the midpoint between bid and ask, the trade is classified as a buyer (seller) initiated trade. Within each of the thirteen half-hour periods during a trading day (from 9:30am to 16:00pm) we calculate the net volume, in thousands of shares, for each stock i, $NVOL_i$.[20]

The slope of a time-series regression of the half-hour returns, $r_{i,\tau}$, on the half-hour net volume measures the price impact, β, in month t.

$$r_{i,\tau} = \alpha_{i,t} + \beta_{i,t} NVOL_{i,\tau} + \varepsilon_{i,\tau} \tag{6}$$

This time-series regression is run for each stock i and each month t.[21] We drop the monthly observation for a ticker if we observe fewer than ten pairs of return and net turnover over the month in question, and exclude penny stocks. A stock is coined to be a penny stock whenever its minimum price during the month falls below one dollar.

As in Breen, Hodrick and Korajczyk (2002) we truncate the highest and lowest beta coefficients using a 10 standard deviation bound. This eliminates on average 2 firms per month. As we would expect, only for a few outliers the price impact goes the wrong direction, i.e. is smaller the higher the net turnover. Breen, Hodrick and Korajczyk (2002) normalize net volume by shares outstanding to

[20] We apply the following filters to the trades and quotes from TAQ: (i) Conditions for a valid trade are a positive recorded price, no TAQ correction indicator, and no entry for special sale conditions. (ii) Following Sadka (2003) we exclude the opening trade, whereas Lee and Ready (1991) exclude the opening trade only if it is not preceeded by a quote. We also discard all trades before 9:30am. (iii) Conditions for a valid quote are that both, bid and ask prices are positive, and the offer price is bigger or equal to the bid price. (iv) The spread is defined as bid price minus ask price. For stocks with a quoted midpoint above $50, observations with a spread exceeding 10% of the quoted midpoint are excluded. Similarly, for stocks with a quoted midpoint of $50 and less, quotes with a spread in excess of 25% are dropped.

[21] Half-hour periods without any valid pair of trade and bid/ask quote are dropped from the sample. For a valid observation of return and net turnover at least two consecutive half-hour intervals are needed.

make the coefficients comparable across firms. This allows to determine the firm characteristics of firms of different liquidity. Our goal is to assess an estimate of trading costs. Hence, we are interested in the price impact per dollar units.

The resulting sample from TAQ contains between 5,175 (April 1997) and 6,562 (March 2002) firms, with an average 5,923 firms per month. Figure 8 shows the mean, median, and the 95% confidence interval of the resulting monthly estimates over time. The coefficients exhibit a remarkable persistence over time. To avoid too much noise due to specific stock market events we take for each stock the average over the calendar year. This still allows for some degree of time variation. A successful stock might, for instance, issue new shares and become more liquid over time. The addition to a major index like the S&P 500 has also an impact on a stock's trading volume and lowers liquidity costs. The slope coefficients are then concatenated to a time series of price impact coefficients for each stock. For 47,244 out of 419,565 monthly observations (11.3%) we observe every half-hour interval within the respective month. The average of the mean and median slope coefficients are very stable over time. The mean is always above the median as the distribution is skewed towards larger price impacts.

Figure 9 exhibits the distribution of the liquidity measure for the nine style categories. As is to be expected the price impact is larger for small stocks. The price impact also increases on average if we move from value to growth stocks. This is partially explained by a larger fraction of Nasdaq stocks among growth stocks. When comparing the average price impact of the funds in Figure 9 with the mean and median price impact on NYSE, AMEX and Nasdaq stocks in Figure 8, we see that funds tend to hold the more liquid stocks on average.

4.2 Probit Analysis

To examine the relationship between fund characteristics and window dressing, we conduct a probit analysis in which we assume that the conditional probability of a portfolio being window dressed is a linear function of characteristics. We do this for each of the identification methods described in section 3. These results are summarized in Table 5.

The characteristics are absolute cumulative fund return over the previous quarter, cumulative excess return over the past quarter relative to the style benchmark, size, number of stocks, reported cash holdings and top 10 holdings as a fraction of net assets, the turnover over the calendar year, the average price impact measure (liquidity costs), the time since fund inception (fund age), the expense ratio, and a flag that indicates whether it is an index fund or not. The remaining explanatory variables control for the Morningstar rating and the nine style orientations.

We find that past poor absolute performance, turnover and style orientation are the most persistent factors. Portfolios selected by our WD identification methodology are more likely to be funds with

high turnover. While we expect that window dressing is causing high turnover, high turnover by itself will lead to large discrepancies in the return differences, but in both directions. Index funds indeed are less likely to be window dressing as one would expect, although the coefficient for WDs from the shape test is not significant. All growth style categories LG, MG, and SG are significantly different from the reference style large/value (LV). Investing in growth stocks is a high risk and high expected return strategy and a investors may need to look closer at holdings information to adjust the returns for risk. Consequently, it will pay off more for a fund to adjust the portfolio before reporting.

5 Liquidity Costs and Momentum Trading

We discuss two competing stories for the explanation of the distinct pattern that we observe around the reporting date: liquidity costs and momentum trading. We measure liquidity costs by using the Breen, Hodrick and Korajczyk (2002) (BHK) estimate for the half hourly price impact. This allows us to approximate the order of magnitude of invisible trading costs if a fund would evenly spread out its trading activity given the reported annual turnover. A simulation experiment shows what pattern we should expect to see from a momentum trader. It turns out that we need to consider the two situations when momentum trading is successful and creates added value to the investor and when the trading activity is not successful. For a successful momentum trader with a time-horizon of half an year the return differences between the hypothetical buy-and-hold strategy of the reported portfolio and the realized fund return would gradually decay towards the reporting date. Even more importantly, the fund return should outperform the simple buy-and-hold portfolio after the reporting date.

5.1 What is the Effect of Liquidity Costs?

Using the BHK liquidity measure we estimate the executions costs if the fund would continuously trade over the year. Section 4.1 above described the methodology to calculate the price impact per half hour as a function of dollar volume traded. To control for liquidity costs we have so far used the market capitalization weighted average of these price impact coefficients for all stocks in the fund portfolio.

The measure of invisible execution costs we use in this subsection is based on the following assumptions:

(i) The fund spreads the trading activity evenly over the entire year.

(ii) The liquidity of the fund portfolio is a good approximation for the invisible execution costs of what the fund trades.

The product of annual turnover and total assets under management (as of year end) returns the annual dollar amount the fund traded. Dividing by the number of trading days and the 13 half-hour periods on a typical trading day, we get the average dollar value traded over a half hour interval, and weighting by the fraction invested in stock i, w_i, the same for an individual stock in the fund portfolio. The dollar amount traded in stock i per half hour is multiplied by the price impact per half hour and aggregating over all stocks in the portfolio estimates a lower bound for transaction costs:

$$\sum_i w_i \times \underbrace{\frac{\text{Price Impact (bps per \$ Traded)}}{\text{1/2 hr Period}}}_{\text{Liquidity Costs}} \times \underbrace{\frac{\text{Turnover (\% p.a.)}\times\text{Assets in \$}}{100\times250\times13}}_{\text{Average \$ Value Traded in Stock } i \text{ per 1/2 hr}} \times w_i$$

where w_i denotes the fraction of total net assets that is invested in stock i.

Figure 10 shows the distributions of these trading costs by investment style. Qualitatively, the invisible execution costs cannot explain the magnitude of the underperformance of NAVs relative to a buy-and-hold strategy we observe for window dressers. A price impact of 0.1 basis points per half hour, which appears to be a high estimate in all distributions, translates into only 1.3 basis points per trading day. Assuming that the liquidity of the portfolio is representative for the traded stocks likely overstates execution costs since funds will turn over the liquid part of their portfolio more often than illiquid stocks. Falkenstein (1996) provides evidence that funds tend to trade in liquid stocks based on the quotient of volume and shares outstanding as a proxy for liquidity.

5.2 A Simulation Experiment for Momentum Trading

A Monte Carlo experiment is used to establish the pattern of average daily return differences we should expect to observe for a momentum trader. We consider three momentum strategies where the momentum trader selects stocks based on their performance over the last 4, 13 and 26 weeks.

We consider a stock universe of 1000 stocks and suppose that the manager holds 100 stocks in his portfolio. Every week the hypothetical momentum trader turns over 10% of his portfolio by exchanging the worst performers he holds for the best performers in the stock universe. Thus his portfolio continues to contain approximately 100 stocks over time.

We consider two scenarios for generating independent stock returns, depending on whether there truly is momentum in stock returns or not.

$$(a) \quad r_{i,t} = \rho_{i,1} r_{i,t-1} + \cdots + \rho_{i,30} r_{i,t-30} + \varepsilon_{i,t}$$
$$(b) \quad r_{i,t} = \varepsilon_{i,t}$$

Innovations to stock returns are assumed to be independent across time and stocks with an annualized standard deviation of 20%. In case (a) we assume that $\rho_1 = \cdots = \rho_{30} = \frac{0.1}{30}$ such that momentum holds true at the one month horizon.

Figure 11 shows the results over the time period 30 weeks before and after reporting. Similar to the empirical results earlier, the geometric mean over non-overlapping weekly intervals is reported.

Two results emerge. The underperformance of the net returns peak at the time horizon of the momentum strategy. Towards the reporting date the difference gradually decreases at a faster rate. Prior to the peak the return difference surges quickly. For the successful momentum trader the NAVs start to outperform a buy-and-hold strategy of the reported portfolio immediately after reporting. After an adaptation period of a few weeks the outperformance remains at the same level for the rest of the half year. It should be noted that a weekly turnover of 10% is rather extreme. This would correspond to a turnover p.a. in excess of 500%.

For a successful momentum strategy the reported portfolio contains by definition recent winners over preceding periods of time. Given that stocks routinely are turned over, the reported portfolio is not expected to be the portfolio the fund held over the quarter. If a fund would naively turn over its portfolio over time without success, then due to brokerage costs and execution costs (bid-ask spreads, price pressure) we would expect the fund to underperform its reported holdings continuously.

6 Hiding Style

A comparison of mutual fund returns to evaluate their performance requires assessing the inherent risk of each manager's portfolio. Given the noise in daily stock returns it is very difficult to describe the risk and return characteristics of a large mutual fund portfolio based on daily returns alone. Self-declared fund objectives are not informative for a peer group evaluation of past performance as can be seen from Table 6. An alternative to the self-declared investment objevtive is to use style classifications. However, many funds rotate their style over time or try to hide their effective style in an attempt to outperform their peers. To assess the risk of an investment in a mutual fund the investor, therefore, may want to inspect the reported fund holdings. We propose a methodology that allows the investor to identify such style hiding by quantifying how much risk the fund manager is taking outside of his style.

6.1 Method to Identify Style Window Dressers

For each reported fund filing we calculate the R-squared of the daily NAV returns with the style benchmark and the R-squared of the buy-and-hold returns of the reported portfolio with the style benchmark. Under the assumption of no window dressing we expect that:

(i) The difference, $R^2_{NAV} - R^2_P$, is symmetrically distributed around zero.

Panel (a) in Figure 12 plots these differences in R-squares. The skewness indicates that for more funds the holdings-based returns have a higher R-square with the style benchmark than the NAV returns. This is consistent with style window dressing. When disclosing the portfolio the fund manager attempts to hide the fact that during the quarter he held stocks outside the style universe.

The identification method for style window dressers is based on the symmetry assumed under the null hypothesis of no window dressing. A style window dresser would not show up in the left tail of the distribution in Panel (a). Thus, we can calculate the 95th percentile of the distribution under the null as, $-q$, where q is the 10th percentile of the distribution of the negative $R^2_{NAV} - R^2_P$ (i.e. the distribution with right truncation at zero). We identify funds above the cutoff, $R^2_{NAV} - R^2_P > q$, to be window dressed. This identification is thus based on a 95% confidence interval. In Panel (b) of Figure 12 these style WD portfolios are below and significantly apart from the 45 degree line.

6.2 The Style Misclassification Problem

Misclassification based on self-declared investment objectives is well documented in the literature. The fund's objective is described in the prospectus and in many cases reflected in the fund name. DiBartolomeo and Witowski (1997) conclude that 40% of the 748 funds in their sample do not match their stated objective.[22] Analyzing 770 actively managed fund over a three-year period 1993-95, Indro, Jiang, Hu and Lee (1998) observe 57% of the funds shifting their style orientation. For the year-end snapshots from 1993-96 with an average of 1,044 mutual funds, Kim, Shukla and Tomas (2000) find that 55% are misclassified. Brown and Goetzmann (1997) report that in their sample 237 of a total of 2,283 funds switched their stated objective over the period from January 1976 to June 1994. Using a procedure with that allows factor loadings to vary over time to accommodate nonlinearity in the factors of actively managed funds, they find that many investment objectives are not uniform and can be broken down into several distinct categories. This leaves the investor with a large degree of uncertainty about the nature of the underlying investments and its risk characteristics.

Table 6 categorizes funds into self-declared 16 fund objectives and compares these objectives with the investment style. The large group of 815 "Growth" funds is split across all nine categories in the style box. Only 614 of these funds fall in the three growth styles ($267 + 97 + 30 = 404$), 151 are classified as value with the balance of 260 funds in the blend style. The alternative classification system of Brown and Goetzmann (1997), that is based on a cross-section of past returns, puts more than half of all "Growth" funds into different categories. The second largest fund group "Growth and Income" invests

[22] The sample covers monthly returns for at least 60 months prior to October 1995.

mainly in large, dividend-paying S&P 500 stocks and are primarily large blend and growth investments. The term growth is misleading as only 6.6%% are classified as funds with a growth orientation. As an example, the Putnam Fund for Growth and Income (ticker PUGIX) has been consistently assigned to large value over the period from 1997 to 2002. Specialty funds are most often clustered in few style subgroups. Technology firms are typical growth stocks with different market capitalizations. With the exception of a single fund, all technology specialty funds are classified as growth funds.

An alternative to the self-declared objective is to rely on style classification systems. However, the experience over the past seven years reveals that one out of five equity mutual funds (21.8% in our sample) is assigned to a different style category within half an year. Table 7 summarizes the style inconsistencies of U.S. domestic equity funds. We observe 4,025 with 27,702 filings over the period 1997-2002. The diagonal elements are the fractions of style consistent funds within each style category. Funds assigned to blend categories most often switch their style. A mere 53.2% of these funds adheres to the investment style over a half-year period since the last holdings disclosure. A large fraction (33.0%), on the other hand, stay invested in medium size stocks. Departures from the initial size class occur far less frequently than shifts between value and growth.[23] The largest moves to investment styles outside their size class are changes of investment style from medium to small growth (6.3%) and vice versa (7.8%). For the 463 reported holdings of 119 index funds (that are not shown explicitly in the table), 86.0% adopt the same style. Especially large-blend index funds, like the Vanguard 500 Index fund, are persistent (96.2%). This is the investment style orientation of all S&P 500 index funds.

7 Conclusions

To assess the performance of a fund, an investor may analyze the past returns of the fund. However, stock returns are noisy and it is very difficult to fully characterize and compare the risk and return trade-off of large stock portfolios. The self-declared fund objective or investment strategy in most cases does not provide much guidance and classifications by style orientation may change quickly over time and make peer group comparisons difficult. Therefore, investors often in part rely on information about the fund's holdings to determine whether a fund has superior stock picking ability.

We show evidence that due to window dressing the reported portfolio holdings may be a misleading indicator of the types of risks the fund took on over the past quarter. We propose a methodology to identify window dressing activity based on net trades between reported portfolios as well as the cumulative return difference between the fund return and the return on a buy-and-hold strategy of the

[23] This is consistent with the changes in the Morningstar style classifications described in Indro, Jiang, Hu and Lee (1998). They investigate changes in the Morningstar style classification of 770 actively managed mutual funds over the period 1993-95.

reported portfolio. We find that growth funds with high turnover and managers with recently poor performance are most likely to window dress. The return pattern we detect for window dressers cannot be reconciled with the manager following a successful trading strategy. After reporting, the pre-expense fund returns on average do not perform better vis-à-vis a buy-and-hold strategy of their own reported portfolio.

Our findings suggest that requiring fund managers to report their holdings more frequently does not necessarily provide more insightful information to the investor. Reporting the dates of the top ten portfolio acquisitions and sales over the preceding quarter would likely protect an investor more effectively from costly window dressing trades. To avoid that portfolio managers with no skill can replicate the trading strategy of successful funds, these trades could be reported with delay.

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	Value	**Blend**	**Growth**	Total
Large	243	373	360	976
	(568)	(796)	(646)	(2010)
	326.2 bn	526.0 bn	289.2 bn	1141.4 bn
	(824.6 bn)	(1129.2 bn)	(702.2 bn)	(2656.0 bn)
Medium	116	68	189	373
	(251)	(165)	(408)	(824)
	32.4 bn	34.1 bn	136.1 bn	202.6 bn
	(110.9 bn)	(63.6 bn)	(215.8 bn)	(390.3 bn)
Small	45	83	139	267
	(110)	(178)	(297)	(585)
	11.1 bn	20.1 bn	41.1 bn	72.3 bn
	(26.0 bn)	(60.0 bn)	(108.0 bn)	(193.9 bn)
Total	404	524	688	1,616
	(929)	(1139)	(1351)	(3419)
	369.7 bn	580.2 bn	466.4 bn	1416.3 bn
	(961.5 bn)	(1252.7 bn)	(1026.0 bn)	(3240.3 bn)

Table 1: Number of funds and total market capitalization in 2001.
The information is shown for the nine investment categories in the Morningstar style box. The values are displayed for the subset of funds where we can match at least 95% of the holdings (including cash) with daily stock returns from CRSP for at least one of the fund's filings in 2001. Numbers in brackets below refer to the full sample of 4,025 U.S. domestic equity mutual funds. The market capitalization is in billions.
Note: The total sample over the period 1997-2002 contains 2,691 (4,025) funds. Out of these, 1.075 (606) funds did not appear in our subset in 2001 or were not assigned to a stylebox.

Variable	**Style**								
	LV	LB	LG	MV	MB	MG	SV	SB	SG
# of Stocks	97	231	78	69	310	80	299	302	156
	(68)	(99)	(55)	(47)	(109)	(67)	(105)	(103)	(99)
Assets (Millions)	1342	1410	803	279	434	422	247	242	296
	(142)	(223)	(123)	(55)	(80)	(83)	(60)	(80)	(115)
Price Impact (bps/$1M)	12.00	9.4	10.8	38.2	63.8	56.3	358.2	220.1	231.1
Cash	2.3%	1.6%	1.7%	2.3%	2.8%	1.7%	2.2%	2.2%	1.6%
Expense Ratio	1.2%	1.1%	1.3%	1.3%	1.1%	1.5%	1.4%	1.3%	1.5%
Turnover	132.1%	66.5%	139.4%	96.3%	149.5%	177.0%	82.5%	78.4%	135.4%
Rating (1-5 Stars)	2.4	1.8	1.4	2.5	2.1	1.6	2.7	2.1	2.0
Index Funds	2.9%	19.8%	1.9%	2.6%	16.2%	1.6%	8.9%	9.6%	5.0%

Table 2: Fund characteristics of 1,616 funds in 2001 by Morningstar style categories.
All fund characteristics are averages over the investement style. Values in brackets indicate medians. The three size classes in the style box are abbreviated as Large, Medium, and Small; the investment orientations are Value, Blend, or Growth.
Note: The total sample over the period 1997-2002, for which 95% of the holdings could be matched, contains 2,691 funds. 1.075 funds did not appear in our subset in 2001 or were not assigned to a stylebox.

		Buying Relatively Strong Stocks			Selling Relatively Weak Stocks		
Month(s)		1	2	3	1	2	3
Buying Relatively Strong Stocks	1	1					
	2	0.821	1				
	3	0.765	0.849	1			
Selling Relatively Weak Stocks	1	0.167	0.182	0.205	1		
	2	0.152	0.122	0.158	0.617	1	
	3	0.127	0.117	0.115	0.615	0.633	1

Table 3: Correlation matrix.
Within nine style universes we classify the top (bottom) 10% performing stocks as relatively strong (weak) stocks. The performance of stocks is ranked using three different, overlapping time horizons: the previous one month, two months, or three months. The table shows the correlations for the three alternative classifications.

	Buyers of Strong Stocks	Sellers of Weak Stocks	NAV Based WDs
Buyers of Strong Stocks	649		
Sellers of Weak Stocks	73	649	
NAV Based WDs	131	56	940

Table 4: Freqency tabulation of the three different window dressed (WD) portfolio identifications.
Using net changes between two adjacent portfolio dates less than 190 days apart, we identify 649 WD portfolios. One set for funds buying recently strong stocks and another equal number selling recently weak stocks. The identification based on cumulative return differences between the hypothetical buy-and-hold strategy of the ex-post reported portfolio and the NAVs over the two weeks leading up to the reporting date classifies 940 portfolios as likely WD. The table shows the relation between the three alternative definitions of WD portfolios. For instance, 73 filings are classified as WD based according to the strong buy and weak sell definitions.

	Shape Test	Sellers of Embarrassing Stocks	Sellers of Losers	Buyers of Winners	Style Rotators
Cum. Return Over Past Quarter	-29.310 **	-18.513	-35.959 *	60.955 **	-14.475
	(0.001)	(0.259)	(0.011)	(0.000)	(0.166)
Cum. Excess Return Versus Style	16.182	20.499	-30.271	-66.772 **	13.432
	(0.352)	(0.535)	(0.209)	(0.004)	(0.479)
Log(Assets)	0.065 *	-0.025	-0.027	0.090 *	-0.194 **
	(0.021)	(0.578)	(0.509)	(0.037)	(0.000)
Log(Number of Stocks in Portfolio)	0.101	-0.355 **	-0.333 **	-0.272 *	-0.366 **
	(0.139)	(0.001)	(0.001)	(0.015)	(0.000)
Log(Turnover)	0.330 **	-0.396 **	-0.479 **	0.958 **	0.442 **
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Expense Ratio	25.761 **	-21.019 **	-5.860	15.509 *	10.350 *
	(0.000)	(0.006)	(0.394)	(0.021)	(0.035)
Log(Price Impact)	0.035	0.138	-0.312 **	0.171	0.161
	(0.600)	(0.208)	(0.003)	(0.101)	(0.056)
Cash Holdings > 1%	-0.056	-0.052	-0.022	0.076	0.022
	(0.125)	(0.376)	(0.687)	(0.172)	(0.604)
Fund Age 3-10 Years	0.110 **	0.024	-0.035	-0.060	0.028
	(0.006)	(0.720)	(0.570)	(0.344)	(0.552)
Fund Age > 10 Years	0.025	0.006	0.121	-0.181	0.025
	(0.729)	(0.960)	(0.286)	(0.087)	(0.758)
Rated by Morningstar	0.064	0.122	0.081	-0.204 *	-0.039
	(0.215)	(0.198)	(0.357)	(0.012)	(0.505)
Indexfund	-0.148	-0.428 **	-0.148	-0.582 *	0.211
	(0.173)	(0.006)	(0.268)	(0.035)	(0.090)
Stylebox 2	0.321 **	0.268 **	0.413 **	0.043	-0.019
	(0.000)	(0.005)	(0.000)	(0.675)	(0.780)
Stylebox 3	0.694 **	0.441 **	0.737 **	0.410 **	0.035
	(0.000)	(0.000)	(0.000)	(0.000)	(0.604)
Stylebox 4	-0.159	-0.019	0.403 **	-0.234	0.092
	(0.117)	(0.896)	(0.002)	(0.118)	(0.410)
Stylebox 5	0.185	-0.277	0.547 **	0.251	-0.170
	(0.104)	(0.196)	(0.001)	(0.119)	(0.192)
Stylebox 6	0.758 **	0.115	0.400 **	0.731 **	-0.009
	(0.000)	(0.420)	(0.004)	(0.000)	(0.923)
Stylebox 7	0.033	-0.048	0.573 **	-0.021	0.112
	(0.805)	(0.820)	(0.004)	(0.915)	(0.486)
Stylebox 8	-0.036	-0.233	0.099	0.165	0.118
	(0.792)	(0.325)	(0.697)	(0.394)	(0.423)
Stylebox 9	0.753 **	-0.008	0.369	0.988 **	-0.132
	(0.000)	(0.968)	(0.064)	(0.000)	(0.307)

Table 5: Fund characteristics of window dressed (WD) portfolios.
The columns contain the estimated coefficients for the WD portfolios based on the shape test (see Section 3.5), top deciles of buyers of recently strong stocks and sellers of recently weak stocks, and the style WD portfolios (Section 6.1). Style orientation is coded as a categorical variable and the coefficients are estimated relative to the category large value (LV). Similarly, the coefficient for Mornigstar rated is relative to not being rated and indexfund relative to not being an index fund.

Fund Objective	**Style**									
	LV	LB	LG	MV	MB	MG	SV	SB	SG	Total
Aggressive Growth	2	7	11	1	1	18	1	2	10	53
Asset Allocation		4	2	1		2			1	10
Balanced	1									1
Equity Income	28	6		5						39
Growth	98	210	267	44	46	97	9	14	30	815
Growth and Income	78	142	14	9	9	3	2	1		258
Small Company				1	6	23	28	63	95	216
Specialty - Communications	6	2	1			1				10
Specialty - Financial	18	1		3	2		1	1		26
Specialty - Health			13			15				28
Specialty - Natural Resources	4			3		1				8
Specialty - Real Estate				44	1		4			49
Specialty - Technology			48		1	29			3	81
Specialty - Unaligned	2		4	2	1			2		11
Specialty - Utilities	5			3	1					9
World Stock	1									1
	243	372	360	116	68	189	45	83	139	1,616

Table 6: Comparison of self-declared fund objectives and style.
The fund objectives and Morningstar style assignments are for the 1,616 funds appearing in our sample in 2001. The three size classes in the style box are Large, Medium, and Small; the investment orientations are Value, Blend, or Growth.
Note: The total sample over the period 1997-2002, for which 95% of the holdings could be matched, contains 2,691 funds. 1.075 funds did not appear in our subset in 2001 or were not assigned to a stylebox.

		Next Reporting								
		LV	LB	LG	MV	MB	MG	SV	SB	SG
Current Reporting	LV	81.8%	9.2%	0.4%	5.6%	0.5%	0.2%			
	LB	13.2%	79.3%	13.5%	0.8%	1.6%	0.5%	0.5%	0.5%	
	LG	0.7%	9.7%	83.4%		4.8%	6.5%			
	MV	4.2%	0.5%	0.1%	78.2%	17.0%	0.5%	3.0%	0.5%	
	MB	0.1%	1.3%	0.2%	10.9%	53.2%	5.3%	1.0%	2.4%	0.3%
	MG			2.5%	0.3%	16.0%	79.2%		1.0%	7.8%
	SV		0.1%		3.7%	1.6%	0.7%	84.2%	16.5%	0.3%
	SB				0.5%	4.8%	0.2%	11.3%	62.6%	10.5%
	SG					0.5%	6.9%	0.0%	16.5%	81.0%

Table 7: Changes in investment style between two subsequent reporting dates.
The table is based on 4,025 funds with 27,702 filings. The highlighted cells on the diagonal contain the fractions of funds that did not change their investment orientation.

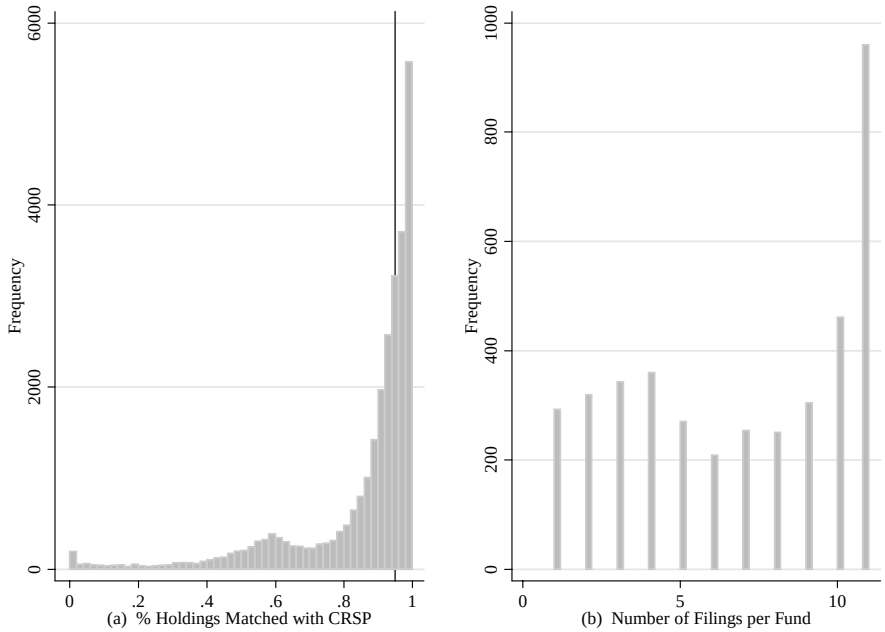

Figure 1: Fraction of positions matched with daily stock returns for the total of 27,702 reported portfolios; and the number of filings per fund for the sample of 2,691 funds with at least 95% matching daily stock returns.
The U.S. domestic equity mutual fund database provided by Morningstar contains 27,702 filings from 4,025 funds. Panel (a) shows the distribution of the fraction of portfolio positions that can be matched with a daily return series from CRSP. The vertical bar indicates the 95% criterion that we apply in determining the subset used to analyze window dressing activity. Panel (b) shows the number of filings per fund that survive our matching criterion. The resulting subset contains 2,691 funds and 11,033 reported portfolios.

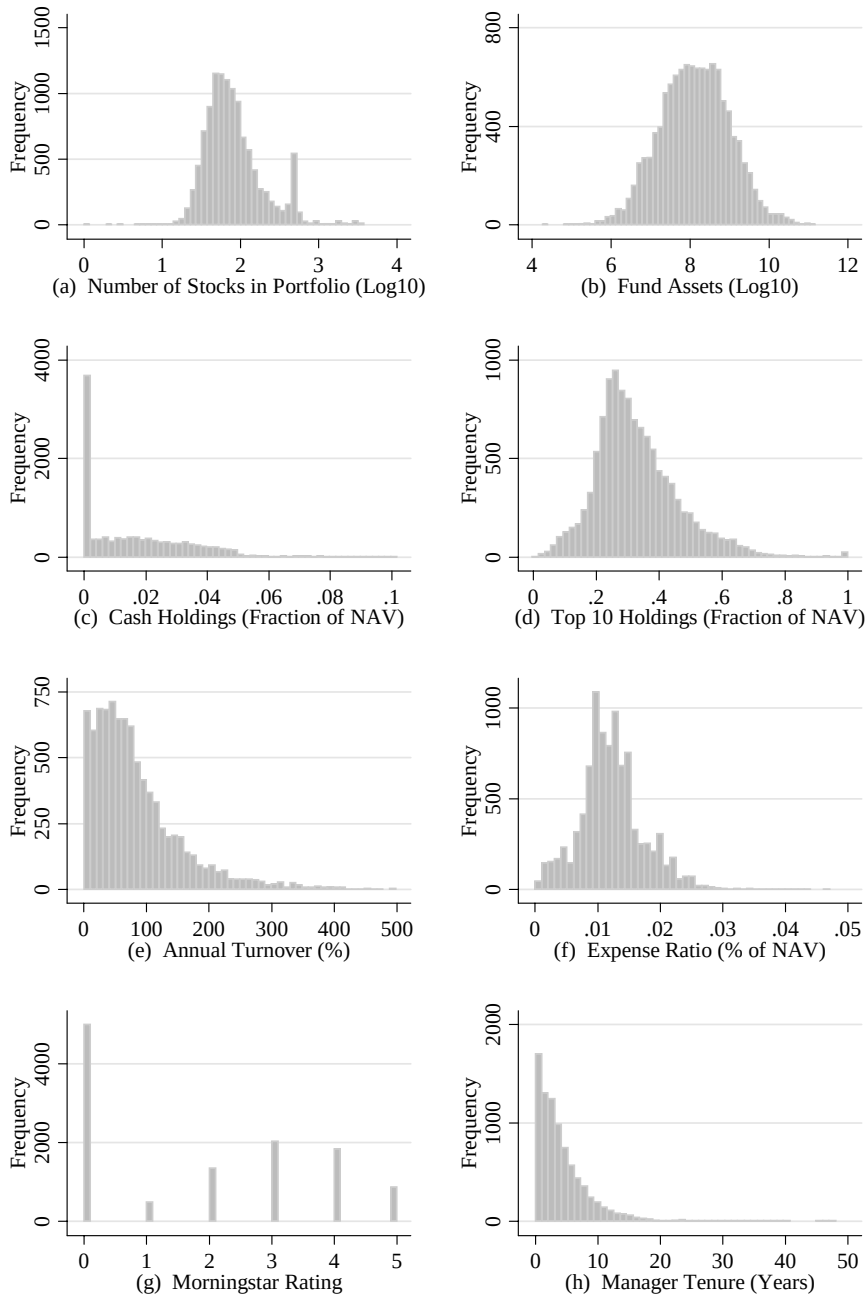

Figure 2: Fund characteristics for the subset of 11,033 filings.
(b) Fund size is measured as the dollar value of the net assets in millions (log10 scale). (c) The fund's total cash and cash equivalent position and the value of its top 10 holdings are expressed as a fraction of total net assets. (e, f) The annual turnover and the expense ratio are defined as a fraction of the average daily net asset values over the past year. The expense ratio includes management fees and asset-based compensations to the distributor and financial adviser. (g) Funds with a history of less than three years are not rated by Morningstar (rating zero). (h) Manager tenure is the number of years the manager has been in charge of a specific fund as of the filing date. The characteristics are shown for the subset of 11,033 portfolios over the six-year period 1997-2002 with 95% matching holdings.

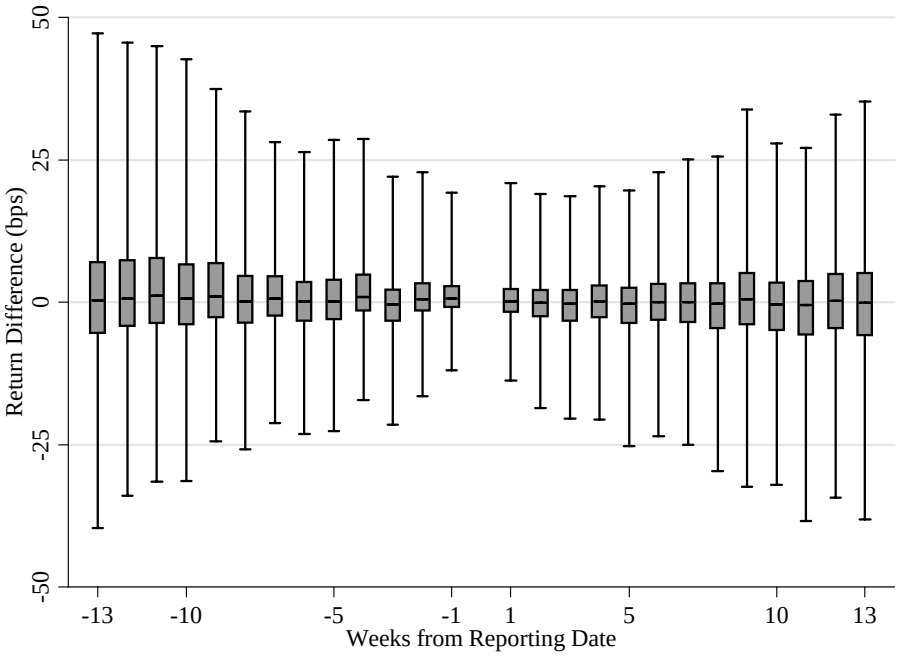

Figure 3: Difference in returns between a hypothetical buy-and-hold strategy of the reported holdings and pre-expense net asset values (NAVs).
For each of the 13 weeks prior to and following the reporting date we calculate the difference between the average daily returns on the reported portfolio (buy and hold) and the fund's realized pre-expense return based on reported NAVs. The difference is positive when the realized fund returns underperform the buy-and-hold strategy of the reported portfolio. The boxplot displays the distribution of these differences in basis points. The horizontal axis shows the weeks before (negative) and after (positive) the reporting date. The gray shaded boxes measure the 25th and 75th percentile, and the line drawn across the median. T-bars correspond to the 2.5 and 97.5 percentiles. The sample consists of 2,691 U.S. domestic equity mutual funds with 11,033 filings over the period from 1997 to 2002.

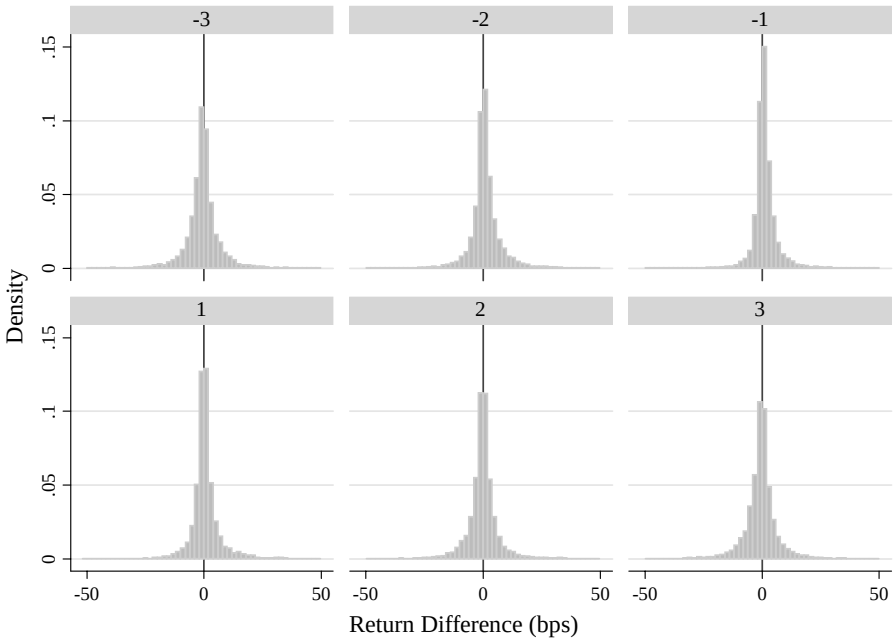

Figure 4: Histograms of average daily return differences.
The return differences measure the daily geometric return over a week for a buy-and-hold strategy of the reported portfolio minus the geometric mean return on the NAVs. The return differences are expressed as basis point (bps) per day. The first row shows the distributions for the three weeks prior to the reporting date (negative week numbers) and the second row the three weeks afterwards. The sample covers 2,691 U.S. domestic equity funds with 11,033 filings from 1997-2002.

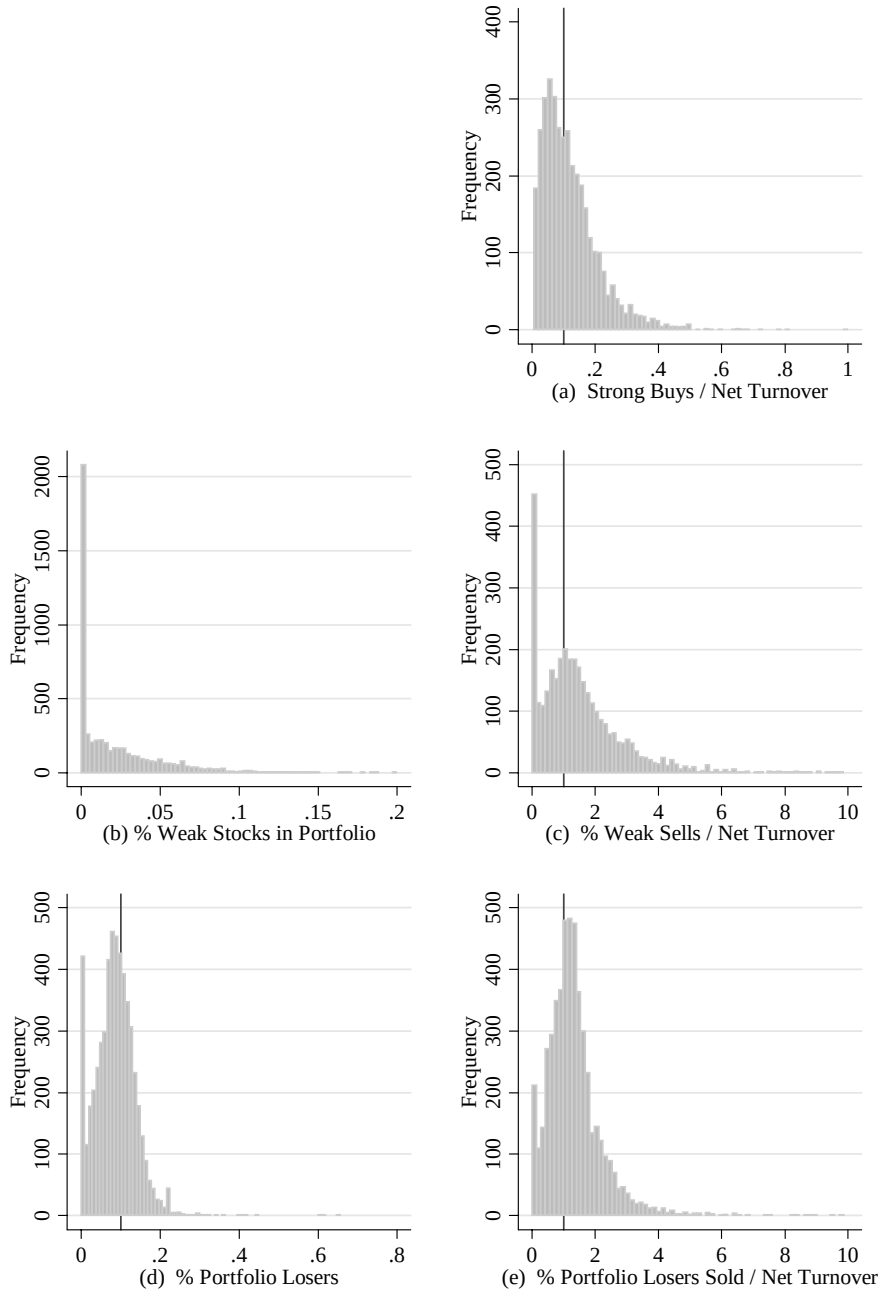

Figure 5: Buying (selling) of recently strong (weak) stocks as a fraction of net changes in holdings. We classify stocks as recently strong (weak) if their cumulative returns over the last quarter are in the top (bottom) 10% within one of the nine style universes. Portfolio losers are defined as stocks with a return that is at least onve standard deviation below the mean return of the fund. The histograms show the distribution of the fraction of NAV that is shifted into (out of) recently strong (weak) stocks between subsequent filings divided by the overall net turnover.

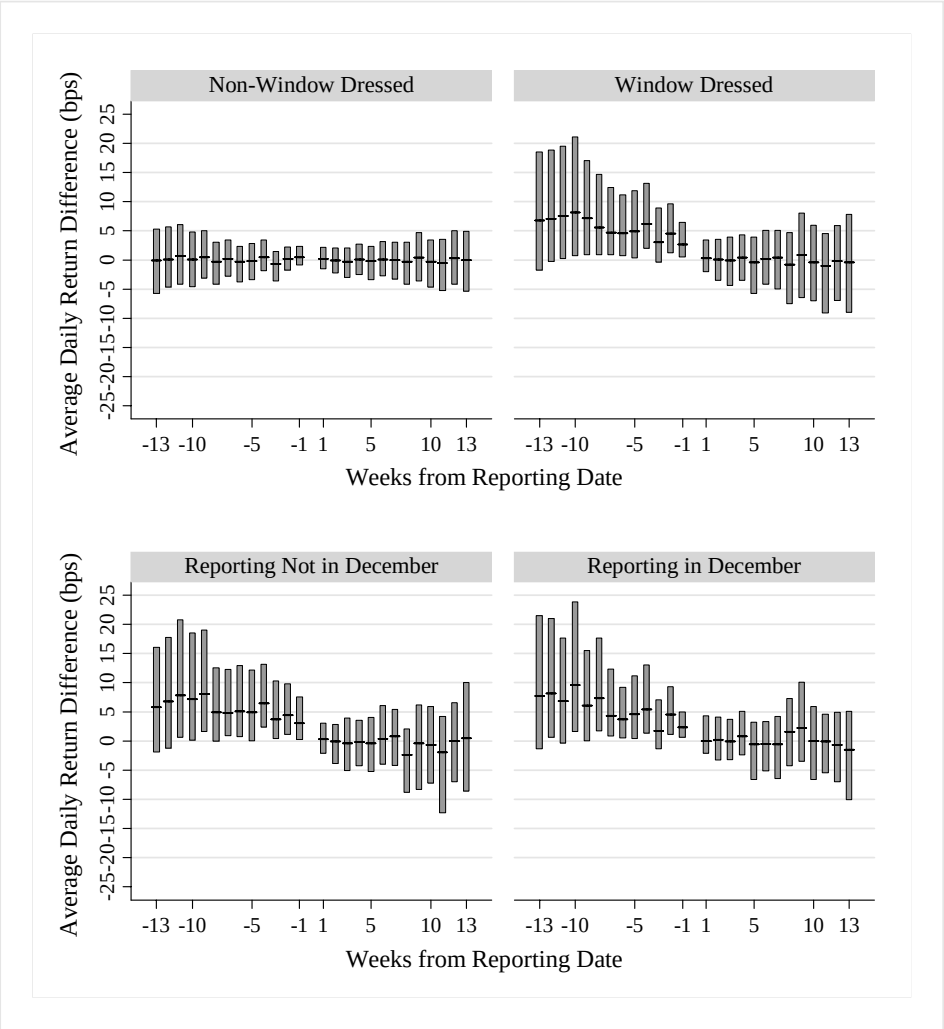

Figure 6: Weekly return differences for the portfolios identified as window dressed based on the shape test.
The graphs show the average daily return differences (returns on a buy-and-hold strategy of the reported portfolio minus the realized NAV returns) over weekly intervals in basis points per day. The results are calculated for the 13 weeks before (negative numbers) and after reporting. Thus, positive numbers indicate that the fund underperforms the reported portfolio in a given week. The gray shaded boxes show the 25th and 75th percentile, and the line drawn across the median. The first row compares the patterns for non-window dressed portfolios [Panel (a)] with the 1,474 window dressed (WD) portfolios based on the shape test [Panel (b)]. Panel (c) shows the weekly return differences for the 871 portfolios that were not reported in December and Panel (d) displays the same graph for the 603 portfolios reported in December.

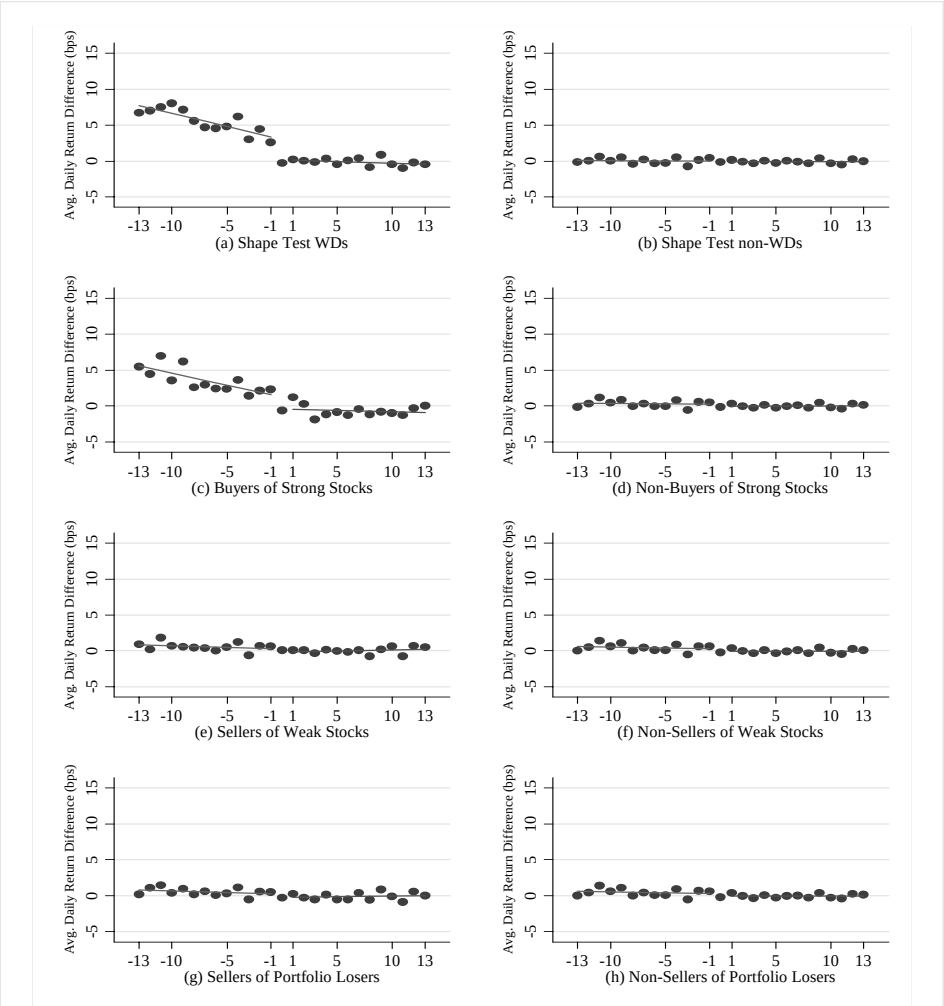

Figure 7: Median return differences for window dressed and non-window dressed portfolios (WDs).
Panels (a) and (b) show the median of the weekly return differences for the 1,474 return WD portfolios from the shape test. A separate line is fitted through the medians for both 13-week periods by least squares. Panels (b) and (c) displays the return difference for the 649 portfolios that were among the top 10% buyers of recently strong stocks over the quarter preceding the reporting date (weeks -13 to -1). Panels (e) and (f) show the same diagram for the top 10% sellers of recently weak stocks, and (g) and (h) for the top sellers of portfolio losers. Portfolio losers are defined as stocks with a return that is at least one standard deviation below the mean return of the fund.

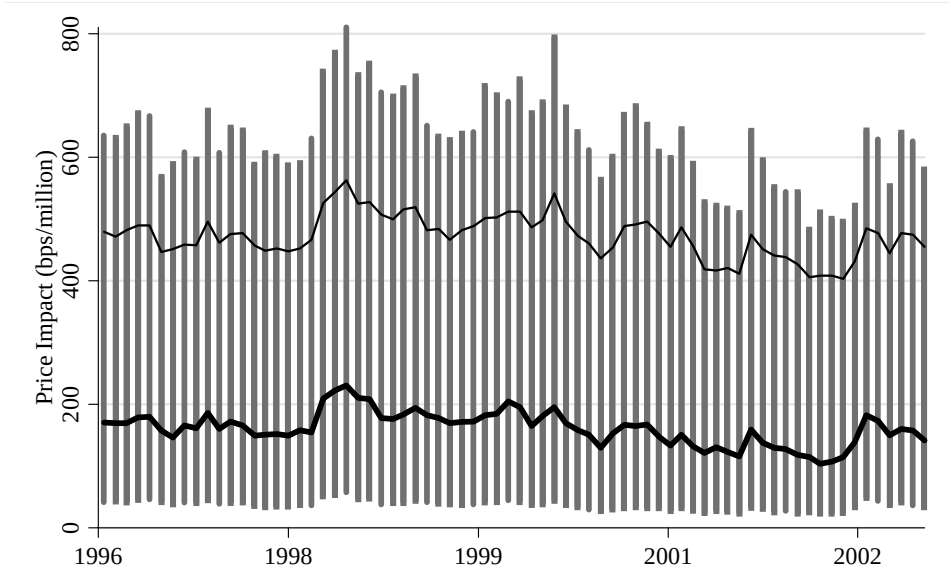

Figure 8: Distribution of monthly price impacts for all stocks on NYSE, AMEX and Nasdaq over the period Jan. 1996 - Jun. 2002.
The liquidity measure estimates the price impact in basis points (bps) when selling shares of the fund's underlying portfolio worth $1 million within a half-hour period. The details are described in Section 3.6. The thick line shows the median and the thin line the mean. The gray bars measure the 25th and 75th percentile.

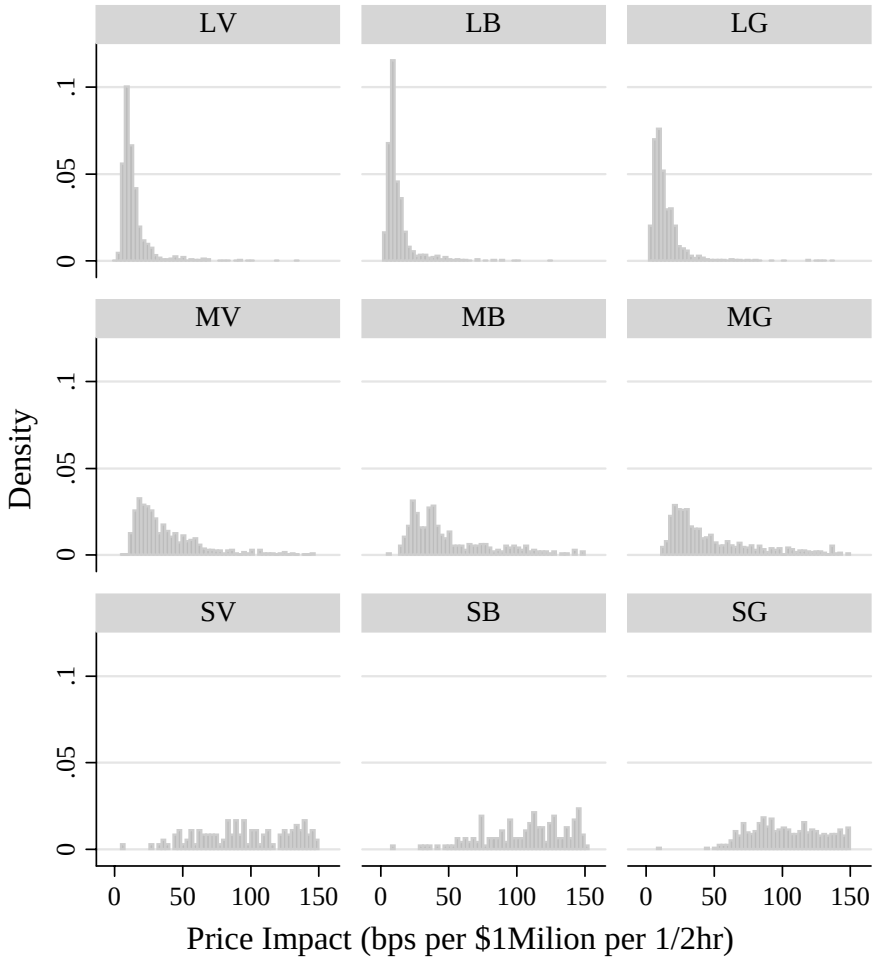

Figure 9: Investment style and average price impact.
Distributions of the Breen, Hodrick and Korajczyk (2002) (BHK) liquidity measure of funds within nine different investment styles. The details are described in Section 3.6. The rows are the three size classes (Large, Medium, and Small), the columns the style orientations (Value, Blend, Growth). The liquidity measure estimates the price impact in basis points (bps) when selling shares of the fund's underlying portfolio worth $1 million within a half-hour period.

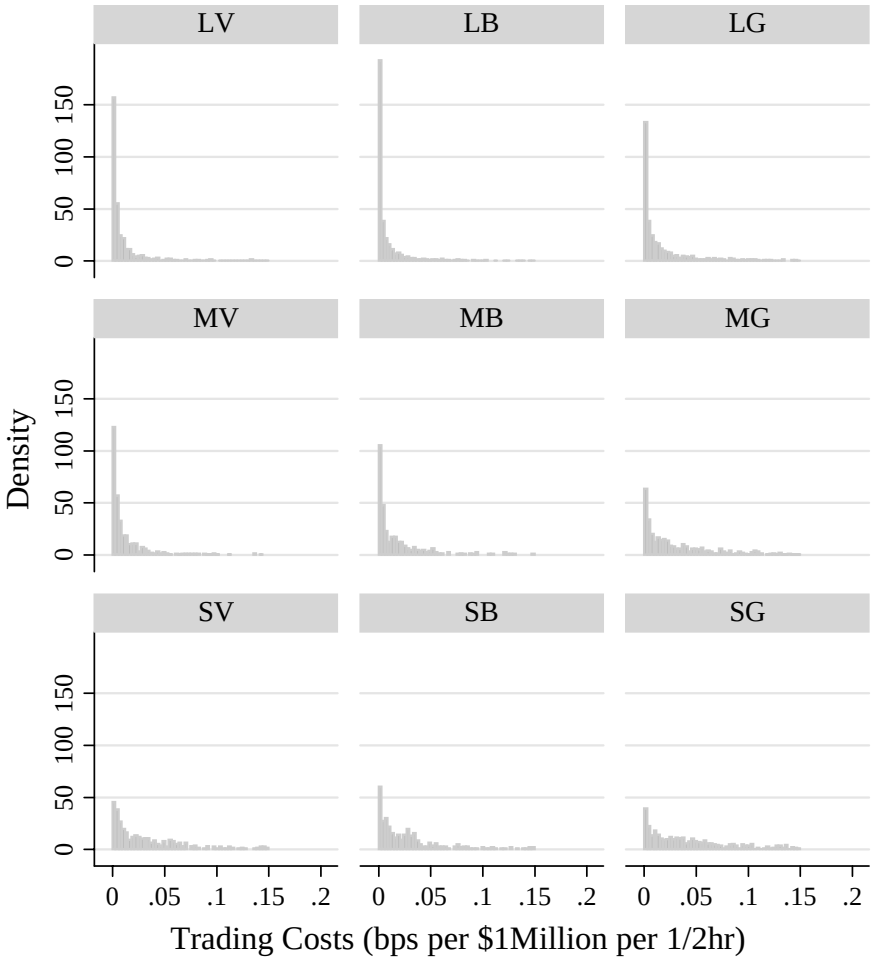

Figure 10: Trading costs per half hour interval.
Given the average annual turnover and the total net asset values we calculate the turnover per half hour. Assuming that the trading activity is evenly spread out over the entire year the half-hour turnover is:
$\sum_i w_i \frac{\text{Price Impact (bps per \$ Traded)}}{\text{1/2 hr Period}} \times \frac{\text{Turnover (\% p.a.)} \times \text{Assets in \$}}{100 \times 252 \times 13} \times w_i$
On a regular trading day there are 13 half-hour intervals from 9:30am to 4:00pm. Multiplying the half-hour volume by the (marginal price impact)/2 returns a lower bound for the invisible transaction costs. As an estimate of the price impact we insert the BHK liquidity measure described in section 3.6. The histograms plot the price impact per half hour by investment style (Large, Medium, Small; and Value, Blend, Growth).

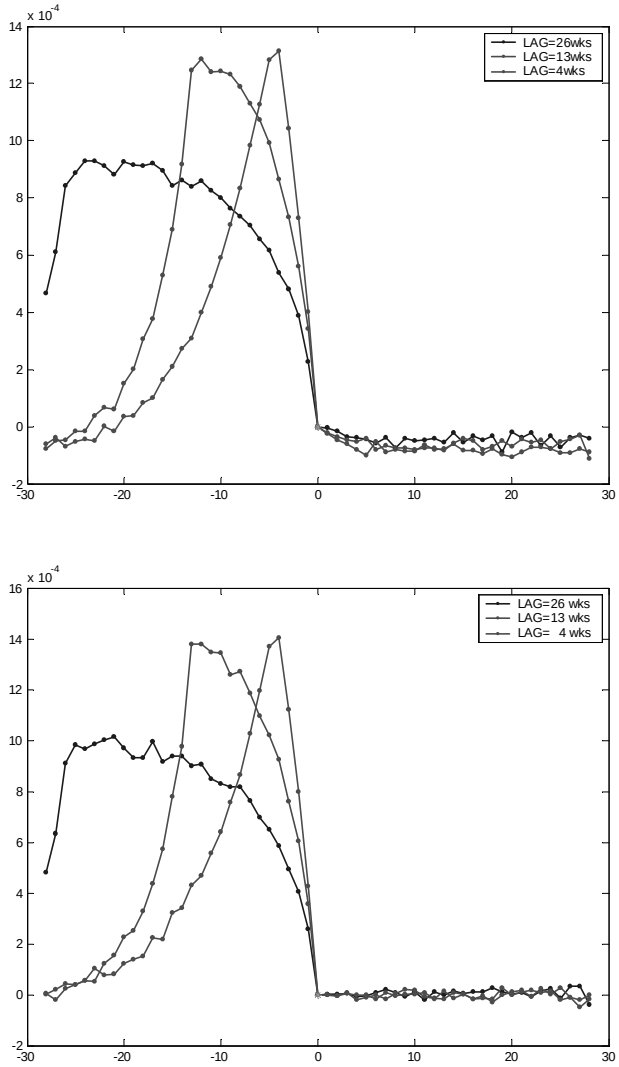

Figure 11: Monte Carlo Simulation for a momentum trader.
Each week the momentum trader switches 10% of his wealth from the worst performing stocks into the best performing stocks over the last 30, 90, and 180 days (LAG). The graphs show the simulations for these three time horizons. The y-axis measures the return difference between the buy-and-hold strategy of the portfolio reported and the realized NAV returns by following the rebalancing strategy. Hence, the difference becomes positive when the fund's NAVs underperform the reported portfolio. The cutoff for the worst and best performing stocks is set to be 10%. Innovations to daily stock returns are drawn from an i.i.d. Normal distribution. In the upper panel the daily stock returns, r_t , are assumed to follow an autoregressive with parameters $\rho_1 = ... = \rho_{30} = \frac{0.1}{30}$, corresponding to 30-day momentum in stocks.
$r_t = \rho_{i,1} r_{i,t-1} + ... + \rho_{i,30} r_{i,t-30} + \varepsilon_t$
Innovations are assumed to be independent across time and the annualized standard deviation 20%. The number of simulations is $N = 5,000$. In the lower panel the daily stock returns are i.i.d. and $r_{i,t} = \varepsilon_{i,t}$, corresponding to no momentum in stock returns.

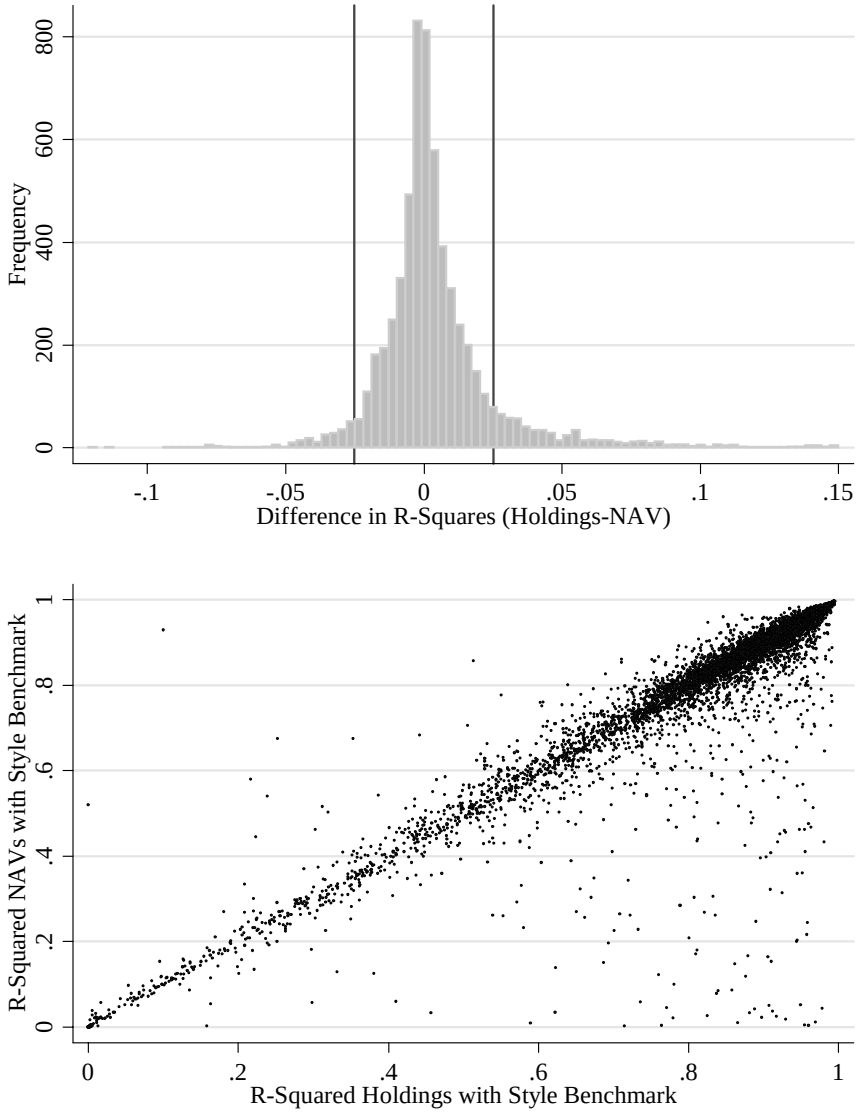

Figure 12: Comparison of R-squares between holdings-based returns with style benchmark versus R-squares between NAV returns and style benchmark.
Panel (a) displays the histogram for the differences in R-squares, $R^2_{NAV} - R^2_P$. The vertical bars indicate the 95% confidence interval calculated under the null hypothesis of no window dressing. Portfolios to the right of the vertical bar (at q) are identified as style WD portfolios. In the scatter plot in Panel (b) the window dressed portfolios are in the lower right corner.